

# Cross Modal Learning Strategies in Rule Based and Information-Integration Category Learning Tasks

Jennifer J. Leib, Joseph Boomer, Mariana V. C. Coutinho, Barbara A. Church, J. David Smith

## Abstract

In recent categorization studies, a distinction has been drawn between Rule-Based (RB) and Information-Integration (II) category learning systems. The RB system is specialized for quickly classifying stimuli on the basis of a single dimension. Alternatively, the II system is optimal for learning stimuli that vary along multiple dimensions. Researchers have traditionally studied these systems by comparing performance between RB and II tasks, which require use of the RB system or the II system, respectively. However, these systems have only been studied within the visual domain. The present research expanded on the established paradigm by asking participants to learn RB and II category tasks for stimuli that vary along visual and auditory dimensions. The participants were able to learn RB tasks faster and with higher accuracy than II tasks, which is consistent with previous research, but they were able to learn the II boundaries even though it required the integration of multiple sensory modalities. The findings suggest that the RB category learning system can discover rules in multiple sensory modalities, and the II learning system can integrate information across senses. The findings expand our understanding of when humans integrate information across sensory modalities, and how this affects categorization.

## Introduction

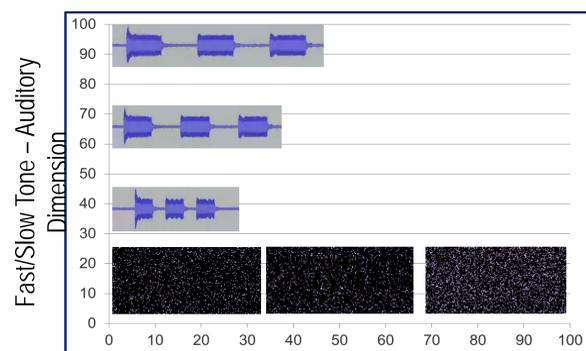
- Humans rely on multiple categorization systems to organize their world.
- Two hypothesized categorization systems are rule based (RB) and information integration (II) categorization.
- This study is the first RB & II categorization experiment to look at cross modal categorization in any species.

## My Question

Are humans capable of using the rule based and information integration systems flexibly, across multiple sensory modalities, or are these systems only capable of attending to one sensory domain at a time?

## Cross-Modal Stimuli

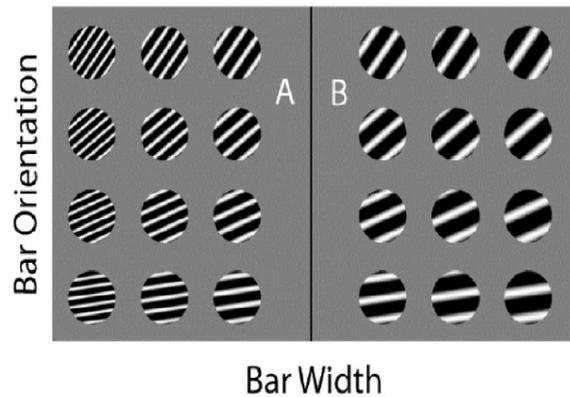
- Cross modal stimuli are stimuli that require multiple senses to be understood.
- In this study, participants see a box full of pixels (X axis) and hear a three beep tone (Y axis).
- Without attending to both of these dimensions, participants are incapable of learning the information integration task.



This graph is a visual representation of the stimulus dimensions for this experiment

## RB Categories

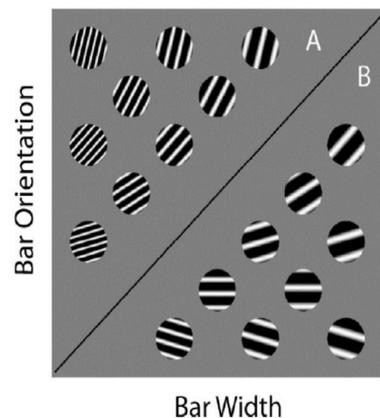
An example of a rule based category structure with two visual dimensions



- The explicit, rule based categorization system is used for classifying RB stimuli.
- RB tasks have a clearly verbalizable rule.
- In the task presented above, all of the category A disks have at least 4 bars, and all of the category B disks have 3 or less bars.
- In this cross-modal study, the rule that participants had to attend to was fast beeping tone (category A) or slow beeping tone (category B).

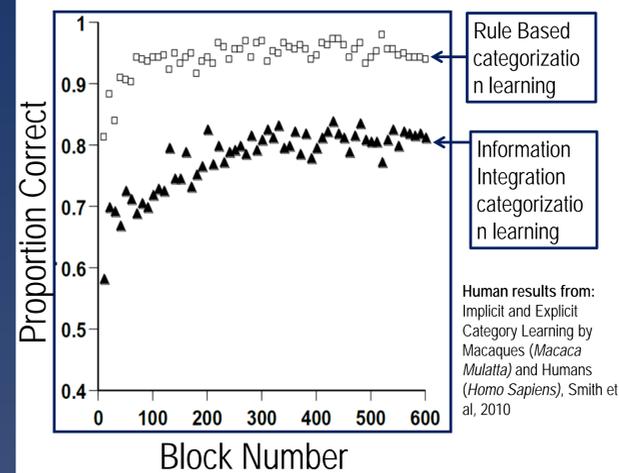
## II Categories

An example of an information integration category structure with two visual dimensions



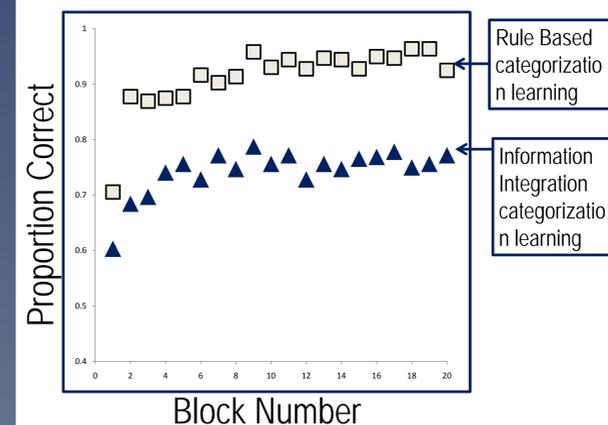
- The implicit, information integration categorization system is used for classifying II stimuli.
- II tasks do not have a clearly verbalizable rule.
- In this task, any one dimensional rule will not be successful.
- Participants must base their categorization strategy on both dimensions.
- In this cross-modal study, participants were required to integrate a beeping tone and a box of yellow pixels.

## Visual RB/II Learning



Human results from: Implicit and Explicit Category Learning by Macaques (*Macaca Mulatta*) and Humans (*Homo Sapiens*), Smith et al, 2010

## Results



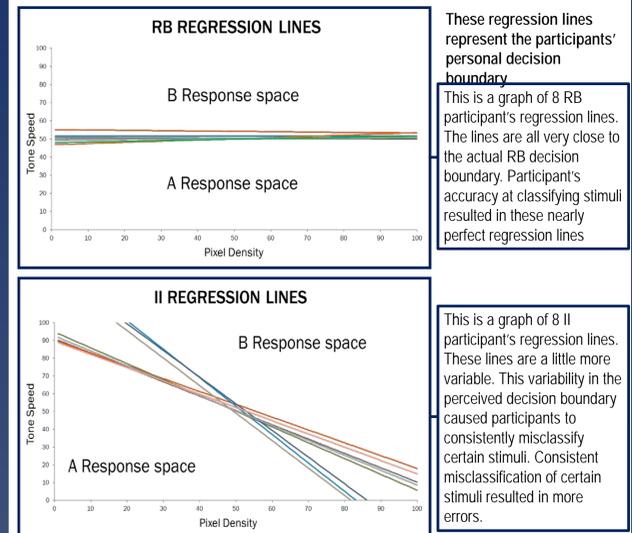
In both conditions, humans displayed statistically significant learning between trials 1-100 and trials 300-400:  
 Information Integration learning =  $t(15) = 2.638, p = 0.009$   
 Rule Based learning =  $t(15) = 3.805, p < 0.001$

- Humans are capable of learning cross-modal RB and II tasks in a way that is similar to tasks that only use visual information.

## Regression Analysis

- A decision boundary is a line that separates category A from B.
- Regression lines are the lines that best fit a participant's personal decision boundary, or where they thought category A and category B were separated.
- According to the analysis of these regression lines, all rule based task participants were able to successfully learn the rule.
- 10 out of 16 information integration task participants were able to learn to integrate the dimensions in the task.
- 6 out of 16 information integration task participants attempted to use a rule.

## Regression Graphs



These regression lines represent the participants' personal decision boundary. This is a graph of 8 RB participant's regression lines. The lines are all very close to the actual RB decision boundary. Participant's accuracy at classifying stimuli resulted in these nearly perfect regression lines.

This is a graph of 8 II participant's regression lines. These lines are a little more variable. This variability in the perceived decision boundary caused participants to consistently misclassify certain stimuli. Consistent misclassification of certain stimuli resulted in more errors.

## Conclusions

- Humans are capable of learning which dimension of a cross-modal stimulus to attend to in a cross-modal rule based categorization task.
- Humans are capable of integrating information across sensory modalities in a cross-modal information integration categorization task.
- Both the RB and II categorization systems are flexible enough to handle multi-modal stimuli in the visual and auditory domain and may be able to attend to cross-modal stimuli that utilize other senses.

## Correspondence

Jennifer J. Leib:  
 jlleib@buffalo.edu

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## 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., & Maddox, W. T. (2005). Human category learning. *Annual Review of Psychology*, 56, 149-178.
- Maddox, W. T., & Ashby, F. G. (2004). Dissociating explicit and procedural-learning based systems of perceptual category learning. *Behavioural Processes*, 66, 309-332.
- Smith, J. D., Beran, M. J., Crossley, M. J., Boomer, J. & Ashby, F. G. (2010). Implicit and explicit category learning by macaques (*Macaca mulatta*) and humans (*Homo sapiens*). *Animal Behavior Processes*, 36, 54-65.
- Smith, J. D., Beran, M. J., Crossley, M. J., Boomer, J. & Ashby, F. G. (submitted). Implicit and Explicit Category Learning by Capuchin Monkeys (*Cebus apella*). *Animal Behavior Processes*.
- Smith, J.D. & Minda, J. P. (1998). Prototypes in the mist: The early epochs of category learning. *Journal of Experimental Psychology: Learning, Memory and Cognition*, 24(6), 1411-1436.