Within-trial variability improves rule-based, not information-integration, category learning

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Abstract

Categorization is a critical component of cognition and contributes to many complex processes, including speech perception. High variability within the environment is thought to initially slow learning while increasing the ability to generalize to novel exemplars. However, little is understood about the mechanisms driving this benefit of variability. The current study investigates the effect of pairing within-category variability with response and feedback within single category-learning trials. Participants who learned categories defined by boundaries orthogonal to the category dimensions—rule-based categories—had superior learning and were better able to generalize to novel exemplars when they were trained with within-trial variability compared to when only a single exemplar was presented on each trial. In contrast, participants who learned categories defined by boundaries involving reliance on both category input dimensions—information-integration categories—showed no enhancement of learning from within-category variability. This draws a distinction between overall variability in the acoustic environment and variability more tightly coupled with response and feedback. The influence of variability as experienced within a single trial differs substantially depending on the nature of the category learning challenge. The results have implications for learning speech categories and for further understanding the mechanisms that contribute to auditory category learning.

Keywords: category learning, variability, rule-based, information-integration

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I. Introduction

Imagine a cat. A specific cat may come to mind —maybe your pet cat or a cat that you saw recently. Or, a more generic cat may pop into your mind. Now, imagine if you had only ever seen orange tabby cats. In this case, it may be a reasonable conclusion that all cats must be orange and white because every cat you had ever seen had been orange and white. Our conceptualization of specific categories is defined by the instances we have experienced from within a category. These instances may be very similar to one another, like orange tabbies, or relatively more variable, like all cat breeds. How we experience within-category variability in the course of category learning ultimately impacts perception and understanding of the categories.

The influence of within-category variability on learning and generalization has been a particular focus in studies of auditory and speech category learning. For example, experiencing exemplars with high acoustic-phonetic variability across category learning has proven to be successful in fostering category acquisition and generalization among adults learning difficult non-native speech categories (Bradlow, Akahane-Yamada, Pisoni, & Tohkura, 1999; Bradlow, Pisoni, Akahane-Yamada, & Tohkura, 1997; Lively, Logan, & Pisoni, 1993; Lively, Pisoni, Yamada, Tohkura, & Yamada, 1994; Logan, Lively, & Pisoni, 1991; Wang, Spence, Jongman, & Sereno, 1999). This acoustic variability typically arises from sampling speech exemplars produced by multiple talkers across multiple phonetic contexts that results in a distribution of experience that samples a wider region of the multidimensional acoustic input space (Lively et al., 1993; Logan et al., 1991) than exemplars drawn from a single talker or phonetic context (Strange & Dittmann, 1984). High variability acoustic sampling has been successful in facilitating learning in several category-learning contexts, including training native Japanese

listeners on difficult English /r/-/l/ categories (Bradlow et al., 1999, 1997, Lively et al., 1993, 1994; Logan et al., 1991; Shinohara & Iverson, 2018; Zhang et al., 2009) and training native English speakers on Mandarin tone categories and general pitch contour categories (Perrachione, Lee, Ha, & Wong, 2011; Wang, Jongman, & Sereno, 2003).

Outside of speech category learning, training with highly variable exemplars has been found to improve infant word learning (Apfelbaum & McMurray, 2011; Galle, Apfelbaum, & McMurray, 2015; Quam, Knight, & Gerken, 2017; Richtsmeier, Gerken, Goffman, & Hogan, 2009; Rost & McMurray, 2009, 2010), second language vocabulary learning (Barcroft & Sommers, 2005), and sequence learning (Gómez, 2002). High variability training is also beneficial to learning outside of the auditory domain. Visual categories sampling large ranges across the exemplar space are learned better than categories with smaller ranges (Maddox & Filoteo, 2011; Perry, Samuelson, Malloy, & Schiffer, 2010). Visual categories are also learned better when participants have seen multiple exemplars from within a category, relative to a single exemplar (Finch, Carvalho, & Goldstone, 2014). The general benefit of variability in a training set has also been found in more complex tasks, such as math problem solving (Braithwaite & Goldstone, 2015; Sanders, Gonzalez, Murphy, Pesta, & Bucur, 2002), reading (Apfelbaum, Hazeltine, & McMurray, 2012), and perceptual skill acquisition in pilots (Huet et al., 2011).

Typically, experiencing high variability across exemplars promotes overall learning (Logan et al., 1991; Perrachione et al., 2011) and improves generalization of learning to novel category exemplars not encountered in learning (Hahn, Bailey, & Elvin, 2005; Liu & Holt, n.d.; Lively et al., 1993; Logan et al., 1991; Maddox & Filoteo, 2011; Posner & Keele, 1968), although it potentially slows initial learning (Amitay, Hawkey, & Moore, 2005; Hahn et al., 2005; Maddox & Filoteo, 2011; Sanders et al., 2002). In general, training with high within-

category variability is thought to improve learning and generalization because a wider range of exemplars allows for a richer representation of within-category information, filtering out more idiosyncratic details of exemplars and providing a better sense of common features within a category. However, although training with high variability is generally successful in inducing robust, generalizable category learning, it is not yet clear which dimensions of variability are significant, or how they benefit learning.

In this regard, a recent study of nonspeech auditory category learning is revealing. Nearly all studies investigating the impact of variability on learning have compared learning across low- and high-variability category exemplars so that the overall variability of a training set differs across groups of learners. However, a recent study demonstrates an impact of exemplar variability on auditory category learning even when the overall variability of the training set is *matched* across groups, but manipulated *within a trial* (Gabay, Dick, Zevin, & Holt, 2015). One group of listeners experienced multiple repetitions of a single category exemplar prior to responding. Another group experienced variable exemplars drawn from the same category prior to responding. Under such a contrast, a simple exemplar-accumulation model might predict no differences in learning across these learning contexts, since *overall* variability in the training set was equivalent. In contrast, Gabay et al. observed that training across trials with within-trial variability led to more robust and generalizable category learning compared to training with no within-trial variability. Thus, Gabay et al. reported that experiencing stimulus variability tightly coupled with feedback and prediction in a learning task supports learning compared to learning the same training set organized without this coupling.

In contrast to nearly all other studies investigating the role of variability in training, Gabay et al. (2015) examined learning across *incidental* training. Participants were not informed

about the existence of auditory categories, they did not make overt auditory category decisions, and they did not receive explicit feedback about categorization; they simply made a speeded response to report the location of the visual target. In their incidental learning task, five sound exemplars from within an auditory category preceded the appearance of the visual target on each trial. Although it was not directly relevant to performance of the simple visual detection task, the auditory categories perfectly predicted the location of the upcoming visual target. Thus, if participants learned the auditory categories it was possible for them to use the auditory categories to predict visual target location and response. Thus, category learning was covertly monitored via a reduction in reaction time to report visual target location across trials and a cost to this reaction time when the category-to-location regularity was destroyed.

In the case for which within-trial sound category variability was present, listeners heard five unique category exemplars prior to the appearance of the visual target. For these trials, the category exemplar variability was tightly coupled with the visual target and the participant's motor response to report its location. Gabay et al. (2015) found that the tight coupling of variability with incidental feedback facilitated learning and generalization, relative to training with no within-trial acoustic variability for which a single category exemplar was repeated five times in a trial. This was true even though participants experienced the same overall category exemplar variability across the course of the two types of training; only the relationship of exemplar variability to the incidental task demands of the visual target detection task differed.

However, since incidental category learning may involve mechanisms distinct from the explicit training with overt feedback (Lim et al. 2014), it is not clear how training with within-trial variability might affect learning on more traditional supervised learning tasks, in which exemplars are more overtly coupled with category decisions and feedback. If it is the case that

experiencing exemplar variability drives learning due to its coupling with task demands and prediction in the incidental learning task, the results should be replicable for learning across overt category decisions and explicit feedback. One objective of the present research is to test this hypothesis to understand how exposure to variability during learning shapes category representations.

An additional objective of the present study is to understand how variability may impact category learning when the categories make greater or lesser demands on selective attention to individual input dimensions. Studies of adult speech category learning would seem to indicate benefits of acoustic variability, whatever its source. However, at a fundamental level input variability is variability across specific input dimensions. So far, understanding the nature of the dimensions that contribute to acoustic variability in the highly multidimensional acoustic space characterizing speech categories has not been a major focus of research. Yet, we know from parallel literatures that category learning can be highly sensitive to the way that exemplars are sampled across input dimensions, even to the extent that learning may be dominated by different underlying mechanisms as a function of the sampling of category exemplars. For example, the Competition between Verbal and Implicit Systems (COVIS) model proposes that there is an explicit, hypothesis-testing system and an implicit, procedural learning system involved in category learning (Ashby, Alfonso-Reese, Turken, & Waldron, 1998) and that these dual systems are optimally suited for learning of distinct samplings of categories across input dimensions.

The explicit system is thought to involve selective attention to single input dimensions, hypothesis testing, rule application, and rule-switching and thus is best suited to learn rule-based (RB) categories, which can be distinguished by verbalizable rules across single input dimensions. RB categories are thought to benefit from overt reasoning about the rules that distinguish the

categories (Ashby & Maddox, 2011; Maddox, Ashby, Ing, & Pickering, 2004). This explicit system involves neural structures that are involved in hypothesis testing, working memory, and feedback processing, such as the prefrontal cortex and head of the caudate nucleus in the basal ganglia (Ashby et al., 1998; Ashby & Maddox, 2011; Nomura et al., 2007).

In contrast, the implicit system is thought to involve procedural learning mechanisms and is best suited to learn information-integration (II) categories, which require pre-decisional integration across multiple input dimensions not benefited by selective attention to individual dimensions. The implicit system involves procedural learning mechanisms in the body and tail of the caudate nucleus and the putamen (Ashby et al., 1998; Ashby & Maddox, 2011; Nomura et al., 2007). As opposed to RB categories, learning II categories does not benefit from overtly reasoning about the relations between the categories and doing so may even impair learning (Ashby & Maddox, 2011; Grimm & Maddox, 2013).

Formulated for understanding visual categorization, the COVIS model has been expanded recently into the auditory system and to both nonspeech and speech categories (Chandrasekaran, Koslov, & Maddox, 2014; Chandrasekaran, Yi, & Maddox, 2014; Goudbeek, Cutler, & Smits, 2008; Goudbeek, Swingley, & Smits, 2009; Roark & Holt, 2018). Researchers have proposed that some speech categories may function as II categories because they are defined by multiple dimensions, are difficult to describe with verbalizable rules, and often require integration across multiple acoustic dimensions (Hillenbrand, Getty, Clark, & Wheeler, 1995; Yi, Maddox, Mumford, & Chandrasekaran, 2014). Here, we attempt to bridge studies on speech category learning that have focused on within-category variability across an experimental training set with studies of category learning through the dual systems perspective. Specifically, experience of within-category variability and the effects on subsequent representations may

depend on the learning mechanisms involved, driven by how the categories relate to the dimensions in the stimulus space and the variability across which they are sampled.

Several studies have examined the effect of high variability across the range of stimuli on visual RB and II category learning. Experiencing category exemplars that sample a large range across stimulus space slows initial learning of II categories relative to exemplars sampling a smaller range, but improves generalization to novel stimuli and exemplars from novel regions of the stimulus space (Maddox & Filoteo, 2011). In contrast, RB category learning is unaffected by altering the variability in the range of the stimuli encountered during training (Maddox & Filoteo, 2011; Maddox, Filoteo, & Lauritzen, 2007; Maddox, Filoteo, Lauritzen, Connally, & Hejl, 2005). The visual II categories in these studies behave similarly to speech categories from other studies—high variability in the training environment initially slows learning, but ultimately leads to better generalization performance relative to low variability. However, as with speech category learning, there have been no investigations of the effects of within-trial variability on II and RB category learning. In the current study, we examine the effect of within-trial variability exposure on II and RB category learning.

There are reasons to believe that experiencing within-trial exemplar variability during training may differentially affect RB and II category learning because the two systems optimal for learning these two category structures differ in their sensitivity to the timing of feedback. RB category learning is robust to disruptions in feedback, including delays in feedback of up to 10 seconds between response and feedback (Maddox, Ashby, & Bohil, 2003; Maddox & Ing, 2005; Worthy, Markman, & Maddox, 2013). In contrast, II category learning is very sensitive to the timing between the presentation of the stimulus, the response, and feedback (Maddox et al., 2003; Maddox & Ing, 2005; Worthy et al., 2013). The sensitivity of II category learning to

feedback timing is thought to be due to the nature of the implicit system and the procedural learning mechanisms involved in learning the stimulus-response associations (Worthy et al., 2013). Due to the timing of the signaling in the procedural learning system, stimuli and responses that occur within 500 ms of the feedback can be reinforced (Valentin, Maddox, & Ashby, 2014; Worthy et al., 2013). For this reason, exposure to multiple exemplars within a single trial may not allow for the procedural learning system to make associations among the multiple exemplars, the motor response, and the feedback. Instead, it could be the case that only the stimulus that occurs within the 500 ms window of the feedback might be strengthened in the association. If this is true, II category learning optimally driven by this implicit system may not benefit from exposure to high within-trial variability.

A resulting prediction is that that II categories will not benefit from within-trial variability due to of the constraints of the timing of the procedural learning system. The timing of the system is such that only the final exemplar played on a trial will become bound with the feedback and form the stimulus-response association in a meaningful way. The other exemplars experienced in a trial will be too distant in time (> 500 ms) from the response or feedback to become linked in a meaningful way. Thus, the prediction is that learning II categories will not be affected by high within-trial variability.

In contrast, another prediction is that that RB categories may benefit from within-trial variability because learning of these kinds of categories via the explicit system is robust to disruptions in feedback. Thus, any delay from presentation of an exemplar to the feedback should not affect how the categories are learned. Additionally, RB categories may benefit from within-trial variability because hearing variability from within a category on a trial may allow participants to discover rules that distinguish categories and guide them to what is relevant and

irrelevant in the variation among exemplars.

The current study investigates the role of exposure to variability in category learning and the formation of representations with the aim of better understanding the factors that drive efficient and robust learning. We examine the impact of training with within-category variability on a single trial on learning information-integration and rule-based categories defined across two nonspeech acoustic dimensions. Using nonspeech dimensions and artificial auditory categories enables complete control over participants' history of experience in order to examine the course of learning. Generalization performance is thought to be supported by variability and has been shown to improve when participants experience within-category variability. Here, we investigate whether the course of learning and its generalization to novel exemplars may be different for information-integration and rule-based categories.

II. Methods

A. Participants

Participants were 87 undergraduates ages 18-25 (56 female, 30 male, 1 unreported) from Carnegie Mellon University who were given either \$10 or partial course credit for participation. Participants were assigned to one of four conditions. The conditions varied on two factors: structure of the to-be-learned categories (information-integration or rule-based) and whether there was within-trial variability during training (present or absent). An additional three subjects were run, but excluded, from analyses because of equipment failure (1 subject from the rule-based without variability condition, 1 subject from the information-integration without variability condition, 1 subject from the information-integration with variability condition). Table I shows the final distribution of participants across conditions. Data for the variability-present conditions were reported in another manuscript (Roark & Holt, 2018).

TABLE I

Number of Participants in Each Condition

<u>Within-trial Variability</u>	<u>Information-Integration</u>	<u>Rule-Based</u>
Present	21	21
Absent	21	21

B. Stimulus Distributions Defining Categories

Figure 1 illustrates the sampling of acoustic exemplars across an input space in two acoustic dimensions to define four auditory categories. Rule-based categories (Figure 1a) were defined distributionally such that two orthogonal decision boundaries, one across each stimulus dimension, could optimally differentiate the categories. Information-integration categories (Figure 1b) were defined across distributions that required integration of the acoustic dimensions for optimal differentiation of the four categories (diagonal decision boundaries).

Figure 1. Stimulus distributions for the (a) rule-based categories and (b) information-integration categories.

The category distributions for each condition were constructed with MATLAB R2014a such that each category was defined by 100 stimulus exemplars sampled from a bivariate normal

distribution of which the means, variance, and covariance matrix were defined for each category (Table II). With four categories per condition, 400 unique stimulus exemplars defined the category learning challenge for each condition. Half of the exemplars from each category were randomly selected for presentation in training; the other half was withheld for testing in the generalization test phase. Sampling was the same for all participants within a condition. Thus, the acoustic variability experienced was the same for all participants within the rule-based conditions and also the same for all participants within the information-integration conditions, whether variability was present on a trial-wise basis or not.

TABLE II

Category Distribution Information

Information-Integration			
<u>Category</u>	<u>Mean (CF, MF)</u>	<u>Variance (CF, MF)</u>	<u>Covariance</u>
Category A	(701.1, 199.4)	(6306.0, 1629.8)	-15.5
Category B	(853.1, 310.7)	(7032.6, 2281.8)	494.9
Category C	(1059.0, 196.5)	(6677.8, 2207.2)	-36.7
Category D	(863.1, 86.8)	(6156.6, 2123.3)	119.8
Rule-Based			
<u>Category</u>	<u>Mean (CF, MF)</u>	<u>Variance (CF, MF)</u>	<u>Covariance</u>
Category A	(735.8, 277.1)	(7198.3, 2600.3)	-201.7
Category B	(922.4, 279.8)	(7496.4, 2082.0)	-804.6
Category C	(749.0, 116.7)	(5081.2, 2251.4)	156.3
Category D	(1007.8, 114.3)	(5102.4, 1891.0)	367.6

C. Stimuli

The acoustic category exemplars were frequency-modulated tones differing in center, or carrier, frequency (CF) and modulation frequency (MF). The dimensions and range of the category spaces were developed based on Holt & Lotto (2006). Each stimulus was created from a

sine wave tone with a particular CF modulated with a depth of 100 Hz at the corresponding MF. The stimuli were root-mean squared (RMS) matched. Stimuli were synthesized in MATLAB R2014a.

D. Procedure

Participants were trained in an overt classification task, under the control of E-prime software (Psychology Software Tools, Inc., Sharpsburg, PA) with acoustic category exemplars presented diotically over Beyer DT-150 headphones.

1. Training Task. Participants were informed that four auditory categories characterized the stimuli and made an overt decision about category identity with a button press. They received overt feedback about their response in the form of a red X in the location of the correct answer. Participants were instructed to use this feedback to inform future responses.

Each of the four training blocks had 96 trials for a total of 384 trials. On each trial, five 300-ms sound exemplars played with a 50-ms inter-stimulus interval. Participants saw four boxes on a computer monitor mounted at eye level. Participants could respond after the final sound. After each response, there was a 500-ms pause after which feedback appeared, in the form of the red X in the location associated with the sound category from which the sound exemplars had been drawn. Previous research has demonstrated that a 500 ms delay impairs neither II category learning nor RB category learning (Worthy et al., 2013). The feedback remained on the screen for 500 ms and was followed by a 1000 ms ITI.

2. Generalization Test. Participants completed a generalization test after training in which they categorized 96 novel category exemplars not experienced in training drawn from the same category distributions on which individual participants were trained (II or RB). Five 300-ms (50-ms ISI) sounds played on each trial, as in training. Responses were possible immediately

following the final sound. Participants received no response feedback during the generalization test.

3. Within-Trial Variability. The presence or absence of within-trial variability is a main variable of interest. As illustrated in Figure 2, five distinct sound exemplars drawn from a single category defined a trial in the Variability-Present condition. The other half of subjects experienced no within-trial category exemplar variability. For this Variability-Absent condition the same exemplar was repeated five times in a single trial. Stimuli during the experiment were selected randomly without replacement. There was no systematic selection of exemplars for Variability-Present trials; each of the five stimuli belonged to a single category and were randomly selected without replacement from that category's exemplars.

Figure 2. Details for the training task including block breakdowns, assignment of categories to locations on screen, and variability manipulation.

III. Results

A. Training Task

1. Data Processing and Normalization. There were slight differences in the optimal

possible accuracies that could be achieved across conditions, as a function of the distributions and decision boundaries that defined the conditions. The II distributions had an optimal accuracy of 90.25% and the RB distribution had an optimal accuracy of 90.5%. To more fairly compare categorization accuracy across conditions, we computed a normalized accuracy whereby

$$\text{Normalized Accuracy} = \frac{\text{Raw Accuracy}}{\text{Optimal Accuracy}}. \text{ Normalized accuracies were used in all analyses.}$$

2. Block-by-block Accuracy. Figure 3 shows the block-by-block categorization accuracy across conditions. A 2 x 2 x 4 repeated-measures ANOVA examining the effect of category distribution (II, RB), within-trial variability (Present, Absent), and block (1-4) revealed effects of learning across training. Categorization accuracy significantly across blocks ($F(3,240) = 5.04, p = .002, \eta_p^2 = .059$), but the trajectory of learning across blocks did not depend on category distribution ($F(3,240) = 2.39, p = .07, \eta_p^2 = .03$), within-trial variability ($F(3,240) = 0.18, p = .91, \eta_p^2 = .002$), or the interaction between category distribution, variability, and block ($F(3,240) = 0.37, p = .78, \eta_p^2 = .005$). The general pattern of learning was similar for all conditions across training blocks.

Figure 3. Normalized accuracy across the four training blocks for participants learning information-integration (left) and rule-based categories (right) with variability absent or present. Performance is shown relative to chance (25%). Ribbon error bars represent the standard error of the mean. Black dots represent the mean and each individual's average accuracy for each block is also shown.

Specifically, much of the learning occurred within the first block. Participants across all conditions performed above chance (25%) in the first block (II-Present: $M = 51.0\%$, $t(20) = 12.4$, $p < .001$, $d = 5.55$, II-Absent: $M = 51.0\%$, $t(20) = 19.2$, $p < .001$, $d = 8.58$, RB-Present: $M = 63.2\%$, $t(20) = 13.6$, $p < .001$, $d = 6.07$, RB-Absent: $M = 47.2\%$, $t(20) = 9.95$, $p < .001$, $d = 4.45$). Although there was a significant main effect of block in the repeated-measures analysis, only the RB without variability condition demonstrated a difference between Block 4 accuracy and Block 1 accuracy ($M = 6.03\%$, $t(20) = 2.09$, $p = .049$, $d = 0.44$). Performance was statistically

equivalent between Block 4 and Block 1 in each of the other conditions (II-Present: $M = 3.41\%$, $t(20) = 1.56$, $p = .13$, $d = 0.33$, II-Absent: $M = 0.00\%$, $t(20) = 0.00$, $p = 1.0$, $d = 0.00$, RB-Present: $M = 4.93\%$, $t(20) = 1.89$, $p = .07$, $d = 0.36$).

As is evident in Figure 3, categorization accuracy during training depended on both on the statistical sampling of the categories and whether exemplar variability was experienced within trials ($F(1,80) = 14.7$, $p < .001$, $\eta_p^2 = .16$). Specifically, the presence of within-trial exemplar variability did not affect learning across for II categories ($F(1,40) = 0.21$, $p = .65$, $\eta_p^2 = .005$). In contrast, categorization of RB categories was significantly more accurate among participants experiencing within-trial variability, compared to no within-trial exemplar variability ($F(1,40) = 26.7$, $p < .001$, $\eta_p^2 = .40$). Although above-chance performance emerged early in training, the differences among conditions were consistent across training. Performance was superior when RB categories were experienced with within-trial variability compared to when that variability was absent. In contrast, the accuracy during learning of II categories did not differ based on whether there was within-trial variability.

B. Generalization Test Accuracy

The main variable of interest is the generalization test accuracy—the ability of participants to successfully transfer category learning to the labeling of novel category exemplars not experienced in the context of training with feedback (Figure 4). Just as for the accuracy during the training task, we used the normalized accuracies for analyses of generalization test performance to more fairly compare RB and II category learning.

Figure 4. Normalized accuracy in the generalization test for participants who learned information-integration (left) and rule-based categories (right) with either variability absent or present. Performance is shown relative to chance (25%) with a point for each individual subject and the mean and standard error shown for each condition in black.

Generalization test categorization accuracy was greater than chance (25%) for all groups, indicative of category learning. Participants who were trained on II categories had an average test accuracy of 52.1% with within-trial variability ($t(20) = 9.59, p < .001, d = 4.29$) and 53.8% without within-trial variability ($t(20) = 18.3, p < .001, d = 8.19$). Participants who were trained on RB categories had an average test accuracy of 67.6% with within-trial variability ($t(20) = 16.6, p < .001, d = 7.43$) and 56.0% without within-trial variability ($t(20) = 15.7, p < .001, d = 7.03$).

Performance in the generalization test depended on the sampling of category exemplars across the input dimensions (II or RB) and whether there was within-trial category variability

($F(1, 80) = 8.49, p = .005, \eta_p^2 = .10$). As predicted, generalization of II category learning was not impacted by the presence or absence of within-trial variability, but generalization of RB category learning was better when there was within-trial variability.

Confusion matrices were constructed to compare how participants responded in the generalization test to the actual category identity of the stimuli presented on each trial. This provides insight into what participants learned about the individual categories and what difficulties they encountered distinguishing between categories. Confusion matrices for participants in the RB conditions are depicted in the top panels of Figure 5, with a key assigning arbitrary letter labels to category input distributions at the right. This visualization demonstrates that the categories that were most confusable by participants in the RB conditions were the B and C categories. These categories differed on both the CF and MF dimensions. Even so, participants frequently responded B when the actual category of the stimulus presented was C, and vice versa. Participants learning RB categories infrequently confused A and D categories with other categories. Examining the confusion matrices across Variability-Present and Variability-Absent training conditions, the benefit of within-trial variability for RB categories appears to be support in differentiating easily confusable categories. Within-trial variability seems to have advantaged generalization of learning to the difficult categories B and C that were more easily confusable according to the confusion matrix data.

Figure 5. Confusion matrices of the response category of the participants in the generalization test relative to the actual stimulus category. (Top) Rule-based distributions. (Bottom) Information-integration distributions. Columns sum to 100% and describe how participants responded relative to the actual category of the stimulus.

Confusion matrices for participants in the II conditions are depicted in the bottom panels of Figure 5, with a key assigning arbitrary letter labels to category input distributions at the right. These categories are distinct from the RB categories as they are arranged differently within the input space. Within the II category distributions, participants learning the II categories demonstrated consistent confusability between the A and B categories and between the C and D categories. These pairs of categories differ on both acoustic dimensions. The confusion matrices

for II participants across Variability-Present and Variability-Absent demonstrate the same pattern of confusability. Whereas training with within-trial variability seemed to increase the distinguishability between the most easily confused categories within the RB distributions, training with variability did not help distinguish confusable categories within the II distributions.

IV. Discussion

The results of this study demonstrate that rule-based categories benefit from training with within-trial variability, but information-integration categories do not. Specifically, training with high variability within a single trial appears to reduce the confusability between categories that are the most difficult to distinguish for RB categories. Even though the overall exemplar variability was identical for all participants, learning RB categories benefitted from exposure to variability within a trial whereas learning II categories was not affected.

A. Within-trial variability did not affect information-integration category learning

Based on the timing dynamics of the implicit procedural learning system, which optimally drives II category learning (Valentin et al., 2014; Worthy et al., 2013), we predicted that II category learning would not be affected by within-trial variability exposure. The implicit system is thought to involve a procedural learning process that learns to assign particular motor responses to regions of perceptual space (Ashby, Paul, & Maddox, 2011; but see Cantwell, Crossley, & Ashby, 2015). The process that leads to feedback sensitivity in the implicit system is potentially linked to dopamine and calcium signaling in the striatum (Valentin et al., 2014; Worthy et al., 2013). Levels of dopamine and calcium peak simultaneously in the striatum within 500 ms of stimulus presentation, providing a potential cellular mechanism for feedback sensitivity in II category learning (Valentin et al., 2014). Because of the signaling processes in the striatum, the ideal delay period between the response and feedback for learning II categories

is 500 ms (Worthy et al., 2013). At this delay period, people learning II categories perform the best and use optimal integration strategies to learn the categories (Worthy et al., 2013). In the current study, the within-trial nature of the exemplar variability meant that only the final sound exemplar was presented was within the optimal 500 ms window for II category learning. Consistent with this conceptualization, the results demonstrate that II category learning and generalization are unaffected by the presence of within-trial variability.

Whereas the timing dynamics of the implicit system lay out a clear prediction for the effects of within-trial variability, they make no prediction for manipulations of variability arising from the range of exemplars. Indeed, contrary to the present results, prior studies have observed that II category learning and generalization benefit from variability when it comes in the form of sampling across a wide range of input space (Maddox & Filoteo, 2011). In the current study, the variability experienced across conditions was equivalent. However, the timing of feedback required for learning in the implicit system was not aligned with the within-trial exemplar variability. The present results are consistent with prior research that demonstrates that II categories cannot be learned without feedback and even feedback delays as long as 1 or 2.5 seconds can drastically disrupt learning (Ashby, Queller, & Berretty, 1999; Maddox et al., 2003; Worthy et al., 2013). The nature of variability and how it relates to the timing of feedback is critical in learning categories that require information integration across input dimensions.

Also relevant in this regard, researchers have examined how grouping and deferring feedback during learning impacts II and RB category learning (Smith et al., 2014). Smith et al. presented participants with blocks of six trials. After each of the six trials, participants made a categorization response. However, feedback was only presented after all six trials and not after each response. The link between the stimulus and response was upheld, but the link between the

stimulus-response and feedback was disrupted. In this context, II category learning was strongly impaired compared to when the link with the feedback was preserved (Smith et al., 2014). In the current study, participants experiencing variability heard five exemplars from within a single category and made a response only after all five exemplars were presented, followed immediately by feedback. Thus, the link between the stimulus-response and feedback was only present for the final sound that was played. The current study complements these previous findings by demonstrating that II category learning is not boosted by within-trial variability.

B. Within-trial variability improved rule-based category learning

In contrast to II categories learned optimally through the implicit system, RB categories learned optimally through the explicit system are robust to disruptions in feedback (Ashby et al., 1999; Maddox et al., 2003, 2004; Maddox & Ing, 2005). Additionally, experience of variability within a single trial may make it easier for participants to generate and test hypotheses about the relations among exemplars within a category, which is particularly beneficial for RB categories (Ashby & Maddox, 2011). Thus, we predicted that learning and generalization of RB categories would benefit from within-trial exemplar variability. The results supported this prediction; learning and generalization performance were higher for participants learning RB categories with within-trial variability than those learning without within-trial variability.

RB category learning is unaffected by manipulations of overall exemplar variability across an input space (Maddox et al., 2007, 2005). RB categories are thought to be learned primarily by creating and selecting hypotheses for rules that distinguish categories (Ashby et al., 1998). Thus, increasing variability across the exemplar space does not disrupt or benefit learning because it does not change the rule defining the category boundary, which can be learned quickly and successfully generalized to novel category exemplars. The distinction between within-trial

variability and overall exemplar variability is critical in understanding the difference between the current findings and the previous findings. In the current study, exposure to multiple exemplars within a single trial may have allowed RB learners to more quickly discover the relevant relationship among exemplars in a way that is supported by the timing dynamics in the explicit system, which can be learned without feedback and can withstand delays in feedback of up to 10 seconds without impairment (Ashby et al., 1999; Maddox et al., 2003, 2004; Maddox & Ing, 2005).

Additionally, in contrast to II category learning, RB learning is unaffected by grouping and deferring feedback (Smith et al., 2014). In Smith et al. RB category learning outcomes were not different when the feedback was given only after six trials of stimulus presentation and response relative to when feedback was immediately presented after each stimulus-response pair. In the current study, five stimuli were presented after which a single response was made. We found that presenting variability this way (grouping five stimuli together with one response and one instance of feedback) improved RB category learning and generalization performance.

It will be informative for future studies to address the potential strategies that participants were using during learning. Overt category learning experiments often employ some kind of decision modeling to assess strategies used during learning (Ashby & Maddox, 1993). However, the traditional decision bound strategy modeling approach cannot accommodate within-trial variability, so it is not possible to compare the present data with strategies estimated from traditional models. However, adapting decision strategy models to accommodate within-trial variability in training will be important for future studies to address to understand how participants' response strategies change across learning.

C. Within-trial variability vs. within-category variability

Examinations of the effect of variability on category learning outcomes have mostly focused on manipulations of the amount of exemplar variability experienced across training (Lively et al., 1993; Logan et al., 1991; Maddox & Filoteo, 2011; Perry et al., 2010). In speech category learning studies, non-native speech produced by multiple speakers across several phonetic contexts leads to learning that generalizes more robustly than less variable speech (Lively et al., 1993; Logan et al., 1991). This has led to a general understanding that variability aids learning and generalization, very broadly speaking. The present results demonstrate that the specific details of how input variability across category exemplars relates to the statistical sampling of categories in the input, and their relationship to response and feedback in training. The current study examined how variability, not in the overall category space, but within a single trial can affect how well categories are learned. There are important distinctions between the present results and those that have led to the general conclusion that variability supports learning.

It is important to recall that the variability experienced across conditions was equivalent in the present experiment. Participants learned from the same category structure and exemplars. Additionally, the categories were complex; each category had many exemplars and exemplars from different categories overlapped in acoustic space. This contrasts with many other studies that use a simplified category environment with relatively few exemplars and little overlap. For instance, in investigating the effect of within-trial variability on learning categories Gabay et al. (2015) constructed relatively simple categories with only 6 exemplars per category. The current work extends the prior findings to more complex category distributions.

Whereas manipulations of overall category exemplar variability have demonstrated that training with high variability categories leads to poorer and slower initial learning, but better generalization (Bradlow et al., 1999, 1997, Lively et al., 1993, 1994; Logan et al., 1991;

Shinohara & Iverson, 2018; Wang et al., 1999; Zhang et al., 2009), manipulating within-trial variability in the present study led to different results. Learning outcomes depended on the nature of the category being learned and whether it required integration of input dimensions and, correspondingly, likely also the learning mechanism involved. RB categories requiring selective attention to a single acoustic input dimension benefitted both in initial learning and generalization from the presence of within-trial variability. In contrast, II categories were unaffected by within-trial exemplar variability in either initial learning or generalization. In all, this suggests that caution is warranted in concluding very broadly that variability improves learning. In fact, the influence of one form of training variability – that experienced within a trial – differs quite substantially depending upon the nature of the category learning challenge. More broadly considering the present results in light of prior research, it is possible to conclude that increases in training set variability interact quite differently with learning mechanisms than adjustments in the relationship of exemplar variability to categorization decision responses and feedback.

V. Conclusion

Variability in experience, and specifically in exposure to within-category variability, changes how categories are learned and the representations that result. We investigated category learning in contexts in which overall category variability was equivalent, but variability was differentially associated with the feedback signal. We found that experiencing category variability within a trial benefitted learning and generalization for rule-based categories but did not affect information-integration category learning or generalization. These results may have implications for speech category learning. Specifically, training second language learners on speech categories or other categories that can be described as rule-based categories with high

within-trial variability may prove a successful strategy for improving learning and generalization. The same benefit may not exist for speech categories that can be better described as information-integration categories.

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