**Common and distinct factors supporting rule-based and information-integration category
learning**

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Abstract

The ability to organize variable sensory signals into discrete categories is a fundamental process in human cognition thought to underlie many real-world learning problems. Decades of research suggests that two learning systems support category learning and poses that categories with different distributional structures (rule-based, information-integration) optimally rely on different learning systems. However, it remains unclear how the *same* individual learns these different categories and whether the behaviors that support learning success are common or distinct across different categories. In the current study, we develop a taxonomy of learning behaviors to investigate which behaviors are stable or flexible as the same individual learns rule-based and information-integration categories and which behaviors are common or distinct to learning success for these different types of categories. We found that some learning behaviors are stable in an individual across category learning tasks (learning success, strategy consistency, learning speed), while others are flexibly task-modulated (learning strategy, learning stability). Further, success in rule-based and information-integration category learning was supported by both common factors (faster learning speeds, higher working memory ability) and distinct factors (learning strategies, strategy consistency). Overall, these results demonstrate that even with highly similar categories and identical training tasks, individuals dynamically adjust some behaviors to fit the task and success in learning different kinds of categories is supported by both common and distinct factors. These results illustrate a need to for theoretical perspectives of category learning to include nuances of behavior at the level of an individual learner.

Keywords: category learning; individual differences; audition; nonspeech; multiple learning systems

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Across a variety of problems in perception and cognition, there is substantial variability across individuals. Individuals vary widely in how well they can learn arbitrary perceptual categories^{1,2}, solve complex logic problems³, or learn a second language⁴⁻⁶. Across such a variety of tasks, some individuals learn quickly while others struggle to learn at all. Here, we investigate what underlies this variability and what behaviors during learning are associated with successful learning. Particularly, we focus on learning of two types of artificial categories that have been proposed to be optimally learned by separable cognitive and neural learning systems: rule-based (RB) and information-integration (II) categories.

RB and II categories are primarily distinguished from one another based on their distributional structure⁷⁻⁹. RB categories can be separated with decision boundaries that are orthogonal to the dimensions (Figure 1a), whereas II categories can be separated with decision boundaries that are non-orthogonal to the dimensions (Figure 1b). As a result of these differences in distributional structure, the requirements for optimal learning are somewhat different. Learning RB categories involves selective attention to the individual stimulus dimensions to create and find rules that separate the categories into quadrants (e.g., Category 1 is low on both temporal and spectral modulation). In contrast, learning II categories involves integration along the dimensions in a way that cannot be easily verbalized by the learner (e.g., Category 1 is low on temporal modulation except when it is not and then it has medium levels of spectral modulation compared to Categories 2 and 3). In this case, making decisions based on the similarity to other encountered stimuli may be a better overall strategy than creating a rule¹⁰. Rather than only applying to artificial experimental contexts, these types of categories may reflect the structure of real-world learning problems that are either distinguished by simple rules (e.g., differentiating tenor and bass singers by pitch frequency range) or more complex rules that

are difficult to describe verbally (e.g., differentiating the sounds /b/ and /p/ by whether the vocal cords during while producing the sound).

Figure 1

Category Distributions

Note. (a) Nonspeech Rule-Based and (b) Information-Integration category structures varying in temporal modulation (Hz) and spectral modulation (cyc/oct). Dashed lines reflect optimal boundaries separating the categories that are either orthogonal (Rule-Based) or non-orthogonal (Information-Integration) to the underlying dimensions defining the stimuli.

The Competition between Verbal and Implicit Systems (COVIS) theory proposes that there are at least two systems involved in category learning separately best-suited for RB and II category learning^{9,11}. The COVIS theory posits that optimal learning of RB categories involves an explicit hypothesis testing system and optimal learning of II categories involves an implicit procedural learning system. The explicit system supports learning through overt hypothesis

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testing, selective attention, working memory, and learning strategies that use verbalizable rules. The explicit system involves a neural circuit including the prefrontal cortex and the head of the caudate nucleus. In contrast, the implicit system supports learning through procedural learning mechanisms, reflected in strategies that are difficult to verbalize. The implicit system involves a neural circuit including the putamen and body and tail of the caudate^{12,13}. Originally developed in the visual modality, the COVIS theory has been expanded to the auditory modality^{14–19}, specifically in the dual learning systems model of auditory category learning²⁰.

Decades of research have demonstrated dissociations between RB and II categories in ways that support the COVIS model^{21–26}. It is important to note that some of these dissociations have been questioned based on methodological or theoretical limitations^{27–29}. However, regardless of whether the evidence supports or refutes a dissociation between RB and II category learning, much of the existing work on RB and II category learning has focused on the possible differentiation of these two learning systems focusing on manipulations that influence group means. As a result, not much is understood about how the same individual learns RB and II categories and whether the behaviors that support learning are common or distinct across these types of categories. In the current work, we introduce an expanded taxonomy of behaviors during category learning that enables a deeper investigation into learning and examine whether behaviors are *stable or flexible* in a learner across tasks and *common or distinct* to RB and II learning success.

Several prior studies have examined RB and II learning in the same individuals. However, these studies have not compared behavior across tasks and, instead, focused on between-subjects comparisons (musicians vs. non-musicians³⁰; Parkinson's Disease patients vs. older adults vs. younger adults³¹), examined RB and II learning in a task-switching context³², or

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focused on how individual differences in cognitive abilities relate to RB and II learning³³. As a result, it is unclear how the same individual approaches and learns RB and II categories. One possibility is that an individual is highly stable in their behavior across different category learning tasks, while an alternative possibility is that an individual flexibly adjusts their behavior depending on the task context or their current state.

To understand what abilities might be commonly related to RB and II learning success, prior lines of work have focused on working memory (WM) capacity. The role of WM in learning has been explored extensively^{34–37}. The focus on WM capacity in RB and II category learning stems from the proposal in the COVIS theory that the explicit system selectively relies on WM capacity and prefrontal cortex, where the implicit system relies on striatal procedural learning mechanisms. In line with COVIS theory's proposal that optimal RB learning involves the explicit system, there is consistent evidence that WM relates to successful RB learning^{33,38,39}. The empirical evidence for the role of WM in II learning is less clear. In line with COVIS theory's proposal that WM may be minimally involved in optimal II learning¹¹, some studies have found that higher WM has minimal or negative impact on II learning^{40–43}. However, others have found that higher WM is better for learning in general, regardless of what type of category is being learned^{33,39,44–46}. Importantly, even when WM capacity has been found to be related to learning, the explanatory power of WM is usually moderate, leaving substantial unexplained variance in category learning ability^{33,39,47}. There is still much to be understood about what supports learning beyond WM capacity.

An important component to understanding individual differences in learning is identifying variability in behavior *during* learning in addition to stable participant abilities like WM capacity. Many studies have demonstrated that even within the same task, participants vary

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in the strategies they use to learn^{2,19,26,30,39,48–52}. Studies grounded in the COVIS theory typically rely on estimation of learning strategies using *decision bound modeling* approaches^{53–55}. Through this framework, decision bound models reveal how participants use the underlying stimulus dimensions to make decisions about category identity and whether learners rely on explicit or implicit learning mechanisms. However, there are meaningful criticisms about estimation of learning strategies through decision bound modeling approaches and whether this actually reflects the involvement of different systems in learning^{56,57}. As a result, there are theoretical reasons to move beyond learning strategy to investigate individual differences in learning behavior.

With the goal of understanding individual differences in learning behavior across tasks and which behaviors are associated with RB and II learning, we present a novel taxonomy of behaviors during category learning (Figure 2). To complement prior approaches, we examine how WM capacity and learning strategies are associated with learning success in RB and II tasks. Going beyond these prior approaches, we examine how an individual's behavior and learning success across different tasks are related to the consistency of one's learning strategy, learning speed, and learning stability.

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Figure 2

Taxonomy of Category Learning Behaviors

Note. (a) Learning success with two representative learners who were more successful (92% maximum cumulative accuracy) and less successful (46% maximum cumulative accuracy). (b) Illustration of the four possible learning strategies: integration based on similarity, random

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guessing, two-dimensional (2D) or one-dimensional (1D) rules. (c) Strategy consistency for two representative learners who had more consistent (92% maximum consistency) or less consistent (46% maximum consistency) strategies. (d) Learning speed illustrated in two representative learners who had faster (0) or slower (282) speeds to reach the group median (black line). Note that their learning success was relatively similar (72% and 62% respectively). (e) Learning stability as the number of correct responses in a row divided by the total number of correct responses over a moving window of 50 trials with two representative learners who are more stable (0.61 maximum stability) or less stable (0.32 maximum stability). Note that their learning success was relatively similar (92% and 90% respectively).

As in prior studies, we examine participants' learning strategies using decision bound models^{54,55}. Using these computational models, we assess the extent to which learners use the dimensions underlying the categories to separate the stimulus space into categories in ways that theoretically rely on explicit or implicit processes¹¹. However, we also move beyond examining the type of strategies learners use to understand how consistently learners apply whichever type of strategy they use during learning.

We also examine how quickly learners reach a baseline level of performance (i.e., learning speed). Learning speed reflects the ability to quickly acquire workable, though likely suboptimal, rules to define the categories. Faster learning speeds may generally provide learners more 'room to grow' and improve their accuracy further. Alternatively, faster learning speeds may be unrelated to overall learning if participants stall in performance and do not continue to improve.

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Finally, we examine participants' learning stability. Learning stability measures the streaks of correct responses while controlling for overall accuracy. Higher learning stability (e.g., longer streaks of correct responses) is generally thought to be reflective of learning, as prior studies have used streaks of correct responses as an overall measure of learning^{40,58–60}. However, it is unclear if stability in performance is related to overall learning when controlling for number of overall correct responses.

This new taxonomy is particularly useful because in addition to providing in-depth descriptions of category learning behavior, we can also make predictions about how these behaviors may be stable in an individual or flexible to a task context and commonly or distinctly related to success in RB and II tasks.

Stability versus flexibility in an individual's learning behaviors

It is possible that these learning behaviors are stable in an individual across tasks, reflecting a stable trait or behavioral tendency. An individual may be stable in how they approach different types of category learning problems. In highly controlled artificial category learning tasks, as we will examine here, the tasks are identical supervised learning tasks with identical feedback, goals, and stimulus dimensions. As a result, there are many reasons to expect that the same person will approach these highly similar tasks in similar ways – applying similar learning strategies, learning similarly quickly, and having similar stability in performance. In support of this prediction, there is some evidence that people tend to use similar simple rule strategies during learning regardless of what is optimal for the task^{23,61}. Here, we will investigate if the *same person* applies similar strategies and learning behaviors during RB and II learning.

Alternatively, these behaviors may be unrelated across tasks and, instead, an individual may modulate their behavior depending on the specific task context. This prediction is well-

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aligned with a dual systems perspective of learning and suggests that how an individual behaves during learning will be modulated based on what is optimal for learning – i.e., whether they are learning RB or II categories. That is, participants will adjust their strategy, how consistently they use their strategy and will differ in how quickly they learn and how stable their performance is depending on what is required of them in the task itself. Additionally, this prediction would also be well-aligned with a perspective that suggests a heavy influence of a learners specific motivational or attentional state within a specific task. For example, a learner may be highly motivated and attentive one day and less so on another day.

Common versus distinct factors in RB and II learning success

Regardless of how these behaviors are related within an individual as they complete different tasks, there are reasons to expect that RB and II learning may be supported by similar behaviors. The underlying task and goals are identical. If this supervised learning task, rather than the distributions of the categories, is a major driver of behavior, we would expect to see many common behaviors relating to success in RB and II tasks. Specifically, learners may find varying levels of success with different strategies and reach higher levels of success the more consistently they apply a strategy, the faster they reach a baseline level of performance, and the more stable their learning is *regardless* of what kind of category they are learning.

In contrast, stemming from the dual systems perspective of COVIS, there are reasons to expect that RB and II learning may be supported by different behaviors. If RB learning relies on the explicit system, RB learning may be uniquely supported by consistent use of explicit-system strategies, faster learning speeds, earlier learning stability, and higher WM capacity. Explicit-system strategies are optimal for RB learning^{8,11}, faster learning speeds may reflect use of explicit-system rules^{58,62}, earlier learning stability should be achieved if learners quickly find

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useful explicit-system rules^{58,63}, and higher WM capacity has been consistently linked to better RB learning^{33,39,48,64}. If II learning relies on the implicit system, II learning may be uniquely supported by consistent use of implicit-system strategies and may be unrelated to learning speed, learning stability, or working memory capacity. Implicit-system strategies are optimal for II learning¹¹, optimal II learning takes longer as it is reliant on slowly building up stimulus-response associations^{8,65}, and higher WM capacity may not be beneficial for II learning^{40–43}.

In sum, we examine RB and II auditory category learning in the same individuals in two separate sessions. We define a taxonomy of behaviors during category learning to assess the relationship between RB and II learning in the same individual and to identify the common and distinct behaviors supporting RB and II learning.

Results

Eighty-six (36 F, $M = 25.4$ years, $SD = 5.04$ years) participants learned both RB and II categories across two sessions separated by at least a week. We first examine how an individual's behavior is related across RB and II category learning to understand *within*-subject variability in learning. We then examine how these behavioral metrics relate to success in a way that is common or distinct across the two tasks.

How does the same person learn in RB and II tasks?

To understand how performance is related across RB and II tasks, we compared overall learning success (Figure 3), learning strategies and the consistency of the application of those strategies (Figure 4), learning speed (Figure 5), and learning stability (Figure 6). These measures provide information of both *how well* participants learn and *how* they learn in these two similar tasks with distinct requirements.

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Learning success. To understand how well participants learned in the RB and II tasks, we computed their cumulative accuracy over a moving window of 50 trials (Figure 3a). This provides information about how performance evolves over time and demonstrates that there is wide variability across individuals. We computed participants' overall learning success as the maximum value of this cumulative accuracy. Overall, we found that participants tended to have higher learning success in the II task ($M = 67\%$) compared to the RB task ($M = 62\%$, $t(85) = 3.55$, $p = .00063$, $d = 0.38$, 95% CI [2.00, 7.11]; Figure 3b). Learning success was strongly correlated across the RB and II tasks ($r(84) = 0.64$, 95% CI [0.50, 0.75], $p < .001$; Figure 3c).

Figure 3

Learning success across nonspeech tasks

Note. (a) Cumulative accuracy over a moving window of 50 trials, first plotted at trial 50. The solid black line reflects mean over all subjects at each trial timepoint. Colored lines reflect variability across individuals. The dashed black line reflects median level of performance within the task (II: 48%, RB: 42%). (b) Learning success as maximum cumulative accuracy across all timepoints for individual subjects. Error bars reflect *SEM*. (c) Correlation between maximum accuracy in the RB and II tasks. Error ribbon reflects *SEM*.

Consistency of learning strategies. Using decision bound models^{54,55}, we examined participants' learning strategies across the 10 blocks of 50 trials (Figure 4a). Specifically, we identified whether learners used one-dimensional (1D) or two-dimensional (2D) rules, hypothesized to be linked to the explicit learning system, an integration strategy combining the dimensions in a way that is difficult for learners to describe verbally and hypothesized to be linked to the implicit learning system, or a random guessing strategy.

Figure 4

Learning strategies across nonspeech tasks

Note. (a) Strategies across blocks. Colors reflect different classes of strategies, which are binned by frequency. Connections between blocks show how strategies changed across blocks. (b) Alluvial plot showing the strategies the same participants used in the final block of the RB and II

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tasks. (c) Consistency of strategy application measured as the percent of a participant's responses that were accounted for by the best-fitting model/strategy. 100% consistency would reflect that the participant clearly applied this strategy with no exceptions in any trials. 25% consistency would reflect a relatively poor fit of the model to the participant's data. Consistency is only measured for non-random strategies. Mean is shown as the black line and individual data is shown in colored lines. (d) Correlation between final-block consistency in the RB and II tasks. Error ribbon reflects *SEM*.

For both RB and II tasks, participants primarily used 2D and 1D strategies to separate the stimuli into categories. The most common strategy for the RB task was the optimal 2D rule strategy, using conjunctive rules along both dimensions. The 2D rule strategy is optimal for RB categories in that the best 2D strategy can yield 97% accuracy in this task. In contrast, the integration strategy is optimal for II categories and can yield 95% accuracy in this task. Even so, the most common strategy for the II task was the 1D rule strategy. While this strategy is not optimal, the best 1D rule strategy can still yield 65% accuracy in this task.

To understand how learning strategies were related across RB and II tasks in the same individual, we examined the types of strategies participants used in the final blocks of the two tasks (Figure 4b). We found that strategies were generally unrelated across the two tasks (30% same strategy, 70% different strategy). However, some types of strategy combinations were more common than others. Among all participants, 40% used a 2D strategy in the RB task and 1D strategy in the II task and 19% used a 1D strategy in both tasks. In all, we found that participants tended to tailor their strategy somewhat to the task at hand, rather than using the same kind of strategy across RB and II tasks in the same underlying stimulus space.

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We were also interested in understanding how *consistently* participants applied whatever learning strategy they used. We calculated their strategy consistency as the proportion of their responses in a block that were accounted for by the best-fitting strategy. Perfect consistency (100%) would indicate that (regardless of whether the strategy was optimal or suboptimal), they applied that strategy consistently. In contrast, a consistency of 25% would mean that they inconsistently applied their strategy, and the best-fitting strategy was not a good fit to the data (i.e., capturing responses around chance levels – 25% for four categories).

Overall, we found that participants varied in the consistency of their strategy application, but generally became more consistent over the course of training (Figure 4c). We compared how consistently the same participant applied their strategies across RB and II tasks by examining the correlation between their final-block consistency across tasks. Note that consistency cannot be calculated for those using random strategies, so participants using a random strategy in either task were not included in the analyses ($N = 6$). There were no significant differences in strategy consistency across RB and II tasks ($t(79) = 1.26, p = .21, d = 0.14, 95\% \text{ CI } [-1.21, 5.41]$) and consistency was relatively strongly correlated across the in RB and II nonspeech tasks ($r(78) = 0.48, 95\% \text{ CI } [0.29, 0.63], p < .001$; Figure 4d). While participants generally used different types of strategies across the RB and II tasks, they tended to apply strategies to a similar degree of consistency across tasks.

Learning speed. We next examined how quickly participants learned to distinguish the categories and reach a median level of performance (Figure 5a). We calculated learning speed as the point in the moving window of 50 trials where the learner first met or exceeded the group median performance over the entire task. We normalized learning speed by the group median for the two tasks (RB: $Mdn = 42\%$, II: $Mdn = 48\%$) to control for inherent differences in difficulty

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across the tasks. A learning speed of zero reflects that the learner reached the median level of performance within the first 50 trials. Additional increases in speed reflect the additional number of trials that it took for the learner to reach the median level of performance. Ten participants who never reached the median level of performance were excluded from the analyses (both tasks, $N = 2$, RB task only, $N = 2$, II task only, $N = 6$). On average, participants reached the median performance after 59 trials in the RB task and 62 trials in the II task. Learning speed was not significantly different in the RB and II tasks ($t(75) = 0.23$, $p = .82$, $d = 0.026$, 95% CI: [-20.2, 25.5]) and learning speed was moderately correlated across the two tasks ($r(74) = 0.29$, 95% CI [0.067, 0.48], $p = .012$; Figure 5b).

Figure 5

Learning speed across nonspeech tasks

Note. (a) Learning speed calculated as the point in the moving window of 50 trials where the learner first met or exceeded the group median for that task over all timepoints (II: 48%, RB: 42%). Zero reflects that they reached this level of performance within the first 50 trials, with additional increases in speed reflecting the additional number of trials it took for the learner to reach the median level of performance. Ten subjects were excluded because they never reached

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the median in either task ($N = 2$), just the RB task ($N = 2$), or just the II task ($N = 6$). Error bars reflect *SEM*. (b) Correlation between learning speed in the RB and II tasks. Error ribbon reflects *SEM*.

Learning stability. The final measure of behavior we examined was learning stability. We calculated learning stability in a moving window of 50 trials as the longest streak of correct responses over the previous 50 trials, normalized by the total number of correct responses over those 50 trials (Figure 6a). Higher values indicate higher performance stability. For example, if two participants responded correctly on 40 of 50 trials, their accuracies would be 80%, but their learning stability would differ based on the maximum number of trials that were correct in a row (e.g., 40/40 correct trials were in a row, stability = 1; 20/40 correct trials were in a row, stability = 0.5). As a result, stability is independent from overall performance. In general, participants were similarly stable across RB ($M = 0.43$) and II tasks ($M = 0.44$, $t(85) = 1.09$, $p = .28$, $d = 0.12$, 95% CI: [-0.050, 0.015], Figure 6b). Learning stability was unrelated across RB and II tasks ($r(84) = -0.090$, 95% CI [-0.30, 0.12], $p = .41$; Figure 6c).

Figure 6

Learning stability across nonspeech tasks

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Note. (a) Learning stability calculated as the longest streak of correct responses over the previous 50 trials, normalized by total number of correct responses over those 50 trials. Mean is shown as a black line and individual data is shown as colored lines. (b) Learning stability as maximum stability in each task for each participant and the group mean. Error bars reflect *SEM*. (c) Correlation between learning stability in the RB and II tasks. Error ribbon reflects *SEM*.

In summary, participants were similarly successful, applied whichever strategy they used at the same level of consistency, and were similarly quick to reach a median level of performance across the two tasks. These behaviors may be consistent within an individual across different tasks, reflecting a stable trait or tendency. However, the same individual also *tailored* their strategy to fit the task at hand and learning stability was unrelated across tasks. This may indicate that these behaviors are modulated by the task and/or by the state learners are in during learning.

What are the common and distinct factors supporting success in RB and II tasks?

By investigating performance across these measures, we achieved a better sense of how an individual learns different types of categories in addition to how well they learn. We next examine which behaviors support success in RB and II tasks and whether these are common or distinct across tasks.

Learning strategies and strategy consistency. Is using a particular type of strategy more beneficial for learning RB and II categories? As a reminder, the optimal class of strategy for RB categories is the 2D rule strategies, whereas the optimal class for II categories is the SPC strategy. Importantly, even if participants are using an ‘optimal’ strategy, they may vary in how successfully they apply that strategy. Here, we ask if a particular type of strategy is associated

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with better learning success for RB and II categories (Figure 7a). Because there are a mixed number of participants using different strategies, we focus on the types of strategies that have a substantial number of participants using the strategies (RB: 2D and 1D; II: Integration, 2D, and 1D).

In the RB task, participants who used an ‘optimal’ 2D strategy had a similar average level of success as those using a 1D strategy (2D $M = 64.4\%$, 1D $M = 60\%$; $t(63.3) = 1.56$, $p = .12$, $d = -0.35$, 95% CI $[-1.23, 9.93]$). It is important to note that there is a fairly wide range of success with either strategy and some participants found high levels of success with an optimal 2D strategy. In the II task, there were significant differences in learning success based on strategy ($F(2, 81) = 29.0$, $p < .0001$, $\eta^2 = 0.42$). According to Bonferroni-corrected post-hoc tests, those using the optimal Integration strategy had significantly higher accuracy than both those using 1D ($p = .010$) and 2D strategies ($p < .0001$). Additionally, those using a 1D strategy were also significantly more accurate than those using a 2D strategy ($p < .0001$). In summary, different strategies are associated with learning success in the RB and II tasks. Specifically, in the RB task, participants could be similarly successful with an optimal 2D strategy or a simpler 1D strategy. In the II task, participants were the most successful when they used an optimal Integration strategy, but also could achieve substantial success with a simple 1D strategy.

Figure 7*Relationship between learning strategies and strategy consistency and success*

Note. (a) Learning success based on final-block strategy for across the two tasks. Error bars reflect *SEM*. (b) Relationship between final-block strategy consistency and learning success based on the final-block learning strategy.

We next examined the relationship between strategy consistency and learning success for the RB and II tasks separately using linear regression models (Figure 7b). In the RB task, the optimal 2D strategy was treated as the baseline and in the II task, the optimal Integration strategy was treated as the baseline. In the RB task, the more consistently participants used a 2D strategy, the more successful they were ($\beta_{\text{consistency}} = 0.80$, $SE = 0.072$, $p < .0001$), but consistency in using a 1D strategy was not related to success ($\beta_{\text{consistency} \times 1D} = -0.76$, $SE = 0.17$, $p < .0001$). In the II task, the more consistently participants used an Integration strategy, the more successful they were ($\beta_{\text{consistency}} = 0.88$, $SE = 0.28$, $p = .0020$). The relationship between consistency and success was not significantly different between Integration and 1D strategies, indicating that the more successfully participants used a 1D strategy, the more successful they were ($\beta_{\text{consistency} \times 1D} = -0.41$, $SE = 0.30$, $p = 0.18$). In the II task, consistency in using a 2D strategy was unrelated to success ($\beta_{\text{consistency} \times 2D} = -0.92$, $SE = 0.41$, $p = 0.029$).

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In all, this demonstrates that the strategies participants use and the consistency of applying a particular strategy are *distinctly* related to success in the RB and II tasks. For RB tasks, the more consistently one can apply a 2D strategy (but not 1D), the more successful they were. For II tasks, the more consistently one can apply an Integration or 1D strategy (but not 2D), the more successful they were.

Learning speed, stability, and working memory capacity. Are particular behaviors or abilities related to success in similar ways in RB and II tasks? Here, we examine how our measures of learning speed, stability, and general WM capacity are related to RB and II learning success. We compared the relationship between these behavioral measures and success in the RB and II tasks using linear regression models.

For both RB and II tasks, learning speed was *negatively* related to learning success (Figure 8a; $\beta_{\text{speed}} = -0.084$, $SE = 0.016$, $p < .0001$). The faster one reached median level of performance, the better their ultimate learning accuracy. Importantly, the relationship between learning speed and success was not significantly different across RB and II tasks ($\beta_{\text{speed*II}} = 0.017$, $SE = 0.020$, $p = 0.40$). Quickly reaching some relatively achievable baseline level of performance gives participants ‘room to grow’ and continue to improve their accuracy, regardless of which type of category they were learning.

Figure 8

Relationship between learning speed, stability, and working memory and success

Note. Relationship between learning success and (a) learning speed, (b) learning stability, (c) working memory capacity (indexed by OSPAN score) across the two tasks.

For both RB and II tasks, learning stability was *unrelated* to learning success (Figure 8b; $\beta_{\text{stability}} = 6.12$, $SE = 14.7$, $p = .68$) and was not significantly different across RB and II tasks ($\beta_{\text{stability} \times \text{II}} = 6.52$, $SE = 21.1$, $p = .76$). Having long streaks of correct responses, controlling for overall accuracy, was not associated with better learning in either task. This indicates that it does not matter *when* correct responses are made, only that the participant makes correct responses.

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For both RB and II categories, WM capacity was *positively* related to learning success (Figure 8c; $\beta_{WM} = 0.34$, $SE = 0.069$, $p < .0001$) and was not significantly different across RB and II tasks ($\beta_{WM*II} = -0.11$, $SE = 0.098$, $p = .25$). The higher one's WM capacity, the better their ultimate learning accuracy, regardless of the type of category.

Figure 9

Summary of the individual behaviors and factors supporting RB and II learning

a	Behavior	Stable or Flexible in an Individual	
	Learning success	Strongly stable ($r = 0.64$)	
	Learning strategy	Flexible (30% same, 70% different)	
	Strategy consistency	Moderately stable ($r = 0.48$)	
	Learning speed	Somewhat stable ($r = 0.29$)	
	Learning stability	Flexible ($r = -0.09$)	

b	common	distinct	Rule-Based	Information-Integration
	Strategy		2D or 1D is best	SPC is best
	Consistency		More consistent 2D (but not 1D) is better	More consistent SPC or 1D (but not 2D) is better
	Speed		Faster is better	Faster is better
	Stability		More stable is not better	More stable is not better
	Working Memory		Higher WM capacity is better	Higher WM capacity is better

Note. (a) Summary of how individual behaviors are stable or flexible across categories. (b)

Summary of behaviors and abilities that are common or distinct in supporting RB and II category learning.

All together, we found evidence for both *stable and flexible* individual behavior in category learning (Figure 9a) as well as both *common and distinct* factors supporting RB and II

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learning (Figure 9b). We found that learning success was strongly stable across tasks, while strategy consistency and learning speed were stable but less strongly so. In contrast, learners were flexible in their learning strategy and stability across tasks. The relationship between learning success and both the type of learning strategy and the consistency of learning strategy was distinct for the two tasks. For RB tasks, 2D or 1D strategies were the most successful, whereas for II tasks, the Integration strategy was most successful. For RB tasks, the more consistently one applied a 2D (but not 1D) strategy, the better one performed, whereas for II tasks, the more consistently one applied an Integration or 1D (but not 2D) strategy, the better one performed. In contrast, learning speed, stability, and WM capacity were commonly related to RB and II learning success. For both tasks, faster learning speeds and higher WM capacity were associated with better learning performance. For both tasks, learning stability was not related to learning outcomes. In sum, our results indicate that performance in RB and II tasks is supported by both common and distinct factors and that performance is supported by both stable individual behaviors and flexible task-modulated behaviors.

Discussion

We examined auditory RB and II category learning within the same individuals. Across perceptually similar auditory categories in procedurally identical tasks, we found that some behaviors were stable within a learner across RB and II tasks: overall learning success, the consistency of a learners' strategy application, and how fast they learn. In contrast, for other behaviors, learners flexibly adjusted their behavior depending on the demands of the task or their state during learning: the types of strategies learners used and the stability of their performance. Further, we found evidence of *both* common and distinct factors supporting RB and II category learning. For both RB and II tasks, faster learning speeds and higher WM capacity were related

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to more successful learning outcomes but consistent application of different types of strategies were related to success in the RB and II tasks. In all, these results indicate that the same person varies in how they approach and learn even in very similar artificial category tasks and that the factors supporting success may relate to both stable individual abilities and more flexible, task-dependent measures such as attention and motivation.

Stable and flexible behaviors during learning in different tasks

The primary focus of the literature on RB and II category learning has been to illustrate a dissociation (or lack thereof) between the types of categories at the group level^{7,8,45}. The present investigation demonstrates that there are differences in how the same individual solves very similar category learning problems, highlighting the necessity for considering learning mechanisms at the level of an individual learner.

In line with prior work, we demonstrated that stable abilities in a learner, such as WM capacity, were reliably related to learning^{33,39,41,43,47,48,50}. We additionally demonstrated that some behaviors during learning are stable across similar tasks completed at least one week apart. These results suggest that to understand the variability in learning, it will be important to understand what factors of the individual relate to these common, stable behaviors (e.g., success, consistency, speed).

Importantly, not all behaviors were stable across different tasks. Learners flexibly modulated their learning strategy and had unrelated learning stability (correct trials in a row) across different tasks. The flexibility in learning strategy here was necessitated by the nature of the task – that is, the tasks had different optimal strategies. Here we demonstrated that rather than being trapped into a similar rule with stimuli that are drawn from identical stimulus spaces, participants could and did flexibly modulate their attention based on the task at hand. Future

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research should explore the extent to which this flexibility relates to overall learning ability and might rely on general cognitive abilities, such as cognitive flexibility⁶⁶.

Learning stability was unrelated across tasks completed a week apart. Our measure of learning stability included the number of correct responses in a row while controlling for overall accuracy. In this way, participants could have similar overall accuracy while one person has high stability, achieving many correct trials in a row, while another has low stability, vacillating between correct and incorrect responses. This distinction is important as this measure was unrelated in the same person across tasks. This indicates that the ability or propensity to get many responses correct in a row relies primarily on task or context-related factors, rather than an individual ability. For example, stability may have varied across days based on a participant's attention or motivation. If learners were able to maintain sustained attention to the task at hand, they would have achieved more correct responses in a row than if they were less able to sustain their attention. Future studies should examine how sustained attention is modulated across tasks and learning states.

Common and distinct behaviors supporting RB and II category learning

Our results do not completely support a generic, single system underlying RB and II category learning where all behaviors that support RB learning also support II category learning, nor do they completely support a rigid dual systems perspective that RB and II are learned by different, competitive systems. Instead, our results demonstrate the need for a hybrid framework wherein there are significant common *and* distinct behaviors supporting RB and II learning.

An important distinction made by the COVIS theory is that the RB and II categories differ in the systems that are *optimal* for learning, rather than what individuals actually do during learning. As such, one might argue that just because there are common behaviors supporting RB

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and II category learning in the current study does not refute the existence of multiple systems of learning. Instead, it could indicate that these common factors are present because people primarily used the explicit system during learning, evidenced by the overwhelming use of 2D and 1D strategies in both RB and II categories. Another possibility is that many participants might not be encouraged to use optimal strategies in the current tasks because these strategies are difficult and effortful. Instead, participants stick with ‘good enough’ strategies that allows them to reach a self-defined ‘acceptable’ level of performance while retaining cognitive resources they might rather be spending on something else. Future studies should examine learning behaviors from initial acquisition to very high levels of accuracy to fully understand how these behaviors might be reflective of similar or distinct processes in RB and II learning.

A taxonomy of behaviors during learning

In the process of defining how behaviors are stable in an individual or commonly related to learning across tasks, we defined a taxonomy of behaviors during category learning. In this way, we provide a framework that can examine the nuances of behavior moving beyond accuracy which cannot provide information about *how* participants learn⁶⁷ and learning strategy which might not itself reflect processes accurately^{56,57}. Further, we move beyond the examination of WM as a single individual difference factor in learning that has now been established to support category learning, likely across different types of categories^{33,39,41,43,47,48,50}. We believe that future studies can benefit from using these measures of behavior to paint a more nuanced picture of behavior, with different predictions based on theoretical models of learning.

In all, our results demonstrate that even with very similar categories and identical training tasks completed over a week apart, we see differences in how an individual solves the problem and the factors that relate to success. These results illustrate a need to move beyond theoretical

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perspectives that rely primarily on group-level behavior and acknowledge the complexity with which individuals approach a learning task.

Methods

Across two sessions separated by at least one week, participants learned nonspeech auditory rule-based (RB) and information-integration (II) categories. The order of the two nonspeech tasks was counterbalanced across participants. As a part of a larger project, all participants also completed a Mandarin tonal speech category learning task at the very end of the experiment (i.e., after the artificial category learning tasks). As this task is unrelated to the predictions of the current study, we do not present or discuss results from this unrelated speech task.

Participants

Participants were recruited through Prolific (www.prolific.co) and the experiment was administered using the online Gorilla Experiment Builder⁶⁸. To assess individual differences in learning across different tasks, we aimed to collect a large sample and arbitrarily settled on recruitment of 100 participants in the first session. Our final included sample size was 86 participants. A post-hoc power analysis was run using the *pwr* package in R⁶⁹ and indicated that a correlation of $r = 0.34$ between performance measures across tasks could be detected with a sample of 86 participants with statistical power at a .90 level with an alpha of .05. One hundred participants ages 18-35 (45 F, $M = 25.3$ years, $SD = 5.05$ years) completed one session and 90 returned for a second session and 86 completed all tasks (36 F, $M = 25.4$ years, $SD = 5.04$ years). The analyses included only participants who completed both RB and II tasks. Participants completed a language and music history questionnaire prior to participating. Participants

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received \$10/hour for their participation for a total of \$20 across two sessions. The study protocol was approved by the Institutional Review Board at the University of Pittsburgh.

Stimuli

Stimuli for the RB and II tasks were artificial nonspeech ripples varying in temporal modulation and spectral modulation (Figure 1). These dimensions are thought to be fundamental properties of complex sounds, including speech⁷⁰ and have been posed as auditory analogs to visual Gabor patches⁷¹. These dimensions have also been used in prior investigations of auditory category learning^{2,38,72,73}. Using nonspeech dimensions enables creation of complex, controlled artificial categories, as is common practice in research on artificial visual category learning (e.g., Gabor patches; line length and orientation). The category distributions were created by sampling from a bivariate normal distribution and had 300 total stimuli (75 stimuli/category). The RB categories can be optimally learned with a conjunctive rule that is orthogonal to the component dimensions (Figure 1A; e.g., high/low on spectral modulation and high/low on temporal modulation). The II categories require rules that are non-orthogonal to the component dimensions, are less clearly verbalizable and include joint consideration of the two dimensions (Figure 1A; i.e., diagonal bounds). Stimuli were 1 sec in duration and RMS amplitude matched to 70dB.

Procedure

Participants completed two sessions, separated by approximately one week ($M = 8.40$ days, $SD = 1.29$ days, range: 7.74 – 13.9 days). In session 1, participants learned one type of category (RB or II) followed by an operation span task⁷⁴ (OSPAN) as a measure of WM capacity. In session 2, participants completed the other task followed by the Mandarin tone learning task. The Mandarin tone learning task was always completed last and is not discussed

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further as part of the current study. At the start of both sessions, participants completed a sound check to ensure that they could hear the sounds and that they were wearing headphones⁷⁵.

Category Learning. In both tasks, participants were instructed to categorize the sounds into four equally likely categories and use feedback to be as accurate as possible. Participants learned the categories across ten 50-trial blocks. Stimuli were selected randomly without replacement and were presented dichotically for a duration of 1 sec. Participants made an untimed categorization response (1, 2, 3, or 4) and received feedback ("Correct"/"Incorrect") for 1 sec followed by a 1 sec ITI.

Working Memory. To understand how differences in WM capacity might relate to learning outcomes, participants completed an operation span (OSPAN) task⁷⁴. The OSPAN task was chosen as a measure of working memory because it can reliably measure WM capacity and relates to other measures of relevant abilities such as attention and complex cognitive abilities⁷⁶.

Participants were shown simple arithmetic problems, reported whether the presented solutions were correct or incorrect (e.g., $(9 + 5) \times 1 = 14$), and were then shown a letter on the screen (e.g., W). Participants saw 15 letter sequences that spanned from three to seven letters. After a full sequence was presented, participants recalled the letters presented in order. The OSPAN score was calculated as the sum of the length of all the correctly recalled spans. For instance, if a participant correctly recalled the sequence of four letters, four points were added to their score. We did not filter the scores based on accuracy of the arithmetic problems as it does not change the validity of working memory span tasks⁷⁷.

Learning Strategies. To assess participants' strategies during learning, we applied several classes of decision bound computational models^{53,55}. Decision bound models divide the two-dimensional space into categories with decision boundaries that are proposed to rely on

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implicit or explicit learning processes¹¹. We fit several classes of models that make different assumptions: an implicit model, explicit two-dimensional (2D) and one-dimensional (1D) rule models, and a random responder model. For all classes of models, the general procedure was that the model takes a set of a participant's responses to the stimuli across a set of trials (e.g., 50 trials) and finds the boundaries in stimulus space that best account for that participant's pattern of responses. The input of the models is the trial-wise response data and dimensional information about the stimuli (i.e., x- and y-dimension coordinates, Figure 1).

The *implicit* Striatal Pattern Classifier model is a neurobiologically grounded model thought to reflect procedural learning mechanisms¹¹. The Implicit model assumes that participants use feedback to learn stimulus-response associations instantiated within the striatum⁷⁸ and can be thought of as complex version of an exemplar model¹⁰. This model has nine free parameters: eight that determine the location of hypothetical striatal units in perceptual space and one that represents the noise associated with the placement of the units. When a participant uses an Implicit strategy, they combine information across both dimensions in a manner that is optimal for II categories.

The second class of models represents *explicit*, hypothesis-testing mechanisms and includes 2D and 1D rule models. 2D rule models place two decision boundaries (one along each dimension) that are combined to determine category membership. When a participant uses a 2D rule strategy, they selectively attend to both dimensions. This type of strategy is optimal for the RB categories. The 2D rule model has three free parameters: two for the boundaries along the x- and y-dimensions and one noise parameter. In contrast, 1D rule models assume that the participant sets three decision boundaries along only one of the dimensions (x-dimension or y-

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dimension) and have four free parameters: three for boundaries along the relevant dimension and one noise parameter.

Finally, the random responder model assumes that the participant guesses on each trial.

The models were run in Python, version 3.7.4⁷⁹. The model parameters were estimated using maximum likelihood procedures⁸⁰ and model selection used the Bayesian Information Criterion (BIC), which penalizes models with more free parameters: $BIC = r * \ln N - 2 \ln L$, where r is the number of free parameters, N is the number of trials in a given block for a given subject, and L is the likelihood of the model given the data⁸¹. Models were fit to each of the ten 50-trial blocks for each participant in both nonspeech tasks (10 blocks x 2 tasks x 86 participants = 1720 total best-fit models). Within each block for each participant, the model with the lowest BIC value was selected as the best-fitting model. Overall, the models captured participants' response patterns better than chance (95% cumulative probability with P success = .25 and $n = 50$, chance = 25 +/- 9%; RB M accuracy: 49%; II M : 52%).

Data Availability

All data and stimulus materials are publicly available at the Open Science Framework and can be accessed at <https://doi.org/10.17605/OSF.IO/TFB6A>. The data were analyzed using R, version 4.2.1⁸², with the R packages *tidyverse*, version 1.3.2⁸³ and *rstatix*, version 0.7.0⁸⁴. Computational models were run using custom scripts in python. Data visualizations were created using the R packages *ggplot2*, version 3.3.5⁸⁵, *ggalluvial*, version 0.12.3⁸⁶, *ggthemes*, version 4.2.0⁸⁷, and *phonTools*, version 0.2-2.1⁸⁸.

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Author Contributions

C.L.R and B.C. conceptualized the study. C.L.R. designed the study and coordinated data collection. C.L.R. pre-processed and conducted formal analysis of the data, conducted computational modeling, and visualized the data. C.L.R. wrote the original draft and B.C. provided review and editing comments. B.C. acquired financial support for the study.

Competing Interests

The authors declare no competing interests.

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