Title
Auditory and visual category learning in children

Journal
Proceedings of the Annual Meeting of the Cognitive Science Society, 44(44)

Authors
Roark, Casey L
Lescht, Erica
Hampton Wray, Amanda
et al.

Publication Date
2022

Peer reviewed

Auditory and visual category learning in children

Casey L. Roark[1,2] (croark@pitt.edu)

Erica Lescht[1] (erica.lescht@pitt.edu)

Amanda Hampton Wray[1] (hamptonwray@pitt.edu)

Bharath Chandrasekaran[1,2] (b.chandra@pitt.edu)

[1]Communication Science and Disorders, University of Pittsburgh, Pittsburgh, PA 15213 USA
[2]Center for the Neural Basis of Cognition, Pittsburgh, PA, 15213 USA

Abstract

Category learning is a fundamental skill across modalities. Previous studies have investigated how children learn categories, primarily focusing on a single modality within a study. As a result, it is not well understood how the *same* children approach category learning tasks across modalities. In this study, we investigate 7–12-year-old children's ability to learn rule-based or information-integration categories in the auditory and visual modalities. Our results indicate that children learn and generalize their knowledge better for visual than auditory categories, regardless of category type, and for rule-based than information-integration categories, regardless of modality. Even so, learning was strongly correlated across all tasks. Children overwhelmingly used unidimensional rule-based strategies to learn, regardless of whether it was optimal for the task. These results demonstrate that there are individual differences in children's ability to learn perceptual categories across modalities and suggest that category learning in children is both category- and modality-general.

Keywords: category learning; development; audition; vision

Introduction

Category learning is a vital skill in human cognition and supports object recognition in the visual modality (Richler & Palmeri, 2014) and speech perception in the auditory modality (Holt & Lotto, 2010). The ability to learn new perceptual categories is important in childhood. For example, children continue learning categories of sounds of their native language until category representations become adultlike around 12 years old (Hazan & Barrett, 2000; Idemaru & Holt, 2013; Nittrouer, 2004; Nittrouer, Manning, & Meyer, 1993; Zevin, 2012). Category learning across modalities is a relevant skill across the lifespan – adults can continue learning novel categories such as the sounds of a foreign language or species of birds for a birdwatching hobby. Prior research has separately focused on how children learn categories in the visual *or* auditory modalities. As a result, little is understood about how development affects learning of categories across both modalities.

Different kinds of categories have their own unique learning demands. While rule-based (RB) categories require selective attention to individual stimulus dimensions, information-integration (II) categories require integration across multiple stimulus dimensions (Ashby & Maddox, 2011). Learning of RB and II categories is thought to be supported by distinct learning mechanisms. RB learning is dependent on explicit learning mechanisms involving prefrontal cortex (PFC) and head of the caudate nucleus in the striatum that rely on selective attention and working memory (Ashby et al., 1998). II learning is dependent on implicit, procedural learning mechanisms involving the putamen and body and tail of the caudate (Ashby et al., 1998).

Critically, these learning systems undergo separate developmental patterns. The system that optimally learns RB categories relies on the PFC, a brain structure that continues to develop even into adulthood (Diamond, 2002; Gogtay et al., 2004; Kolk & Rakic, 2022). Cognitive abilities like selective attention and working memory that are involved in RB learning also continue developing in childhood (Cowan, 2016; Gathercole, 1999; Plude, Enns, & Brodeur, 1994). In contrast, the procedural system that optimally learns II categories relies on the caudate nucleus, which is thought to be fully adultlike by 7 years old (Casey et al., 2004). Procedural learning systems are adultlike by 10 years old (Diamond, 2002).

In prior work, children have been compared to adults in their ability to learn RB and II categories separately in the visual and auditory modalities. For RB categories, the general finding across modalities is that adults are better at learning than children (Huang-Pollock, Maddox, & Karalunas, 2011; Rabi & Minda, 2014b; Reetzke, Maddox & Chandrasekaran, 2016). RB learning also improves with age – adults are better at RB auditory category learning than adolescents (13-19-years-old), who are themselves better at learning than children (7-12-years-old; Reetzke et al., 2016). The developmentally sensitive ability to selectively attend to dimensions that are relevant and ignore dimensions that are irrelevant during learning is thought to underlie their poorer RB learning (Rabi & Minda, 2014a; Rabi, Miles, & Minda, 2015). Specifically, children often use suboptimal rule strategies during RB learning.

For II categories, learning patterns across development are less clear. There is some evidence that, like RB learning, children are also worse at II learning compared to adults

In J. Culbertson, A. Perfors, H. Rabagliati & V. Ramenzoni (Eds.), *Proceedings of the 44th Annual Conference of the Cognitive Science Society.*

(Huang-Pollock et al., 2011; Roark & Holt, 2019). Poor II performance has been proposed to occur because of inefficient transition from rule-based to task-appropriate procedural strategies, a switch that is proposed to be controlled by the PFC (Huang-Pollock et al., 2011). Further, during II learning, many children perseverate with task-inappropriate rule-based strategies, as a result, learning is worse (Huang-Pollock et al., 2011; Roark & Holt, 2019).

However, there are reasons to expect that children may learn II categories just as well as adults. While children ubiquitously struggle to learn RB categories relative to adults, studies have found that 3-8-year-old children can be just as accurate as adults in learning visual categories that cannot be described with a simple rule (Minda, Desroches & Church, 2008; Rabi & Minda, 2014a; Rabi et al., 2015). In the auditory modality, one study found that while many 5-7-year-olds perform worse than adults and struggle to learn II categories, children who used adultlike procedural strategies performed just as well as adults (Roark & Holt, 2019).

Children may also be better at II learning than RB learning because the way they allocate their attention may be well-aligned with the demands of II learning. While children are unequivocally poorer than adults at selectively attending to individual dimensions, children may be better at integrating across dimensions than adults (Kemler & Smith, 1978; Smith & Kemler, 1978). Children are also sometimes better than adults at seeing patterns between stimuli (Lucas et al., 2014) and are better at remembering information from category-irrelevant dimensions than adults (Deng & Sloutsky, 2016; Plebanek & Sloutsky, 2017; Sloutsky & Fisher, 2004). Children also use more exploratory strategies than adults in explore-exploit tasks (Blanco & Sloutsky, 2019, 2020; Liquin & Gopnik, 2022). During category learning, whereas adults tend to exploit rule-based strategies, children use similarity or family resemblance strategies (Minda & Miles, 2009). These behaviors may be particularly useful for II category learning, where participants must integrate across multiple dimensions to determine category identity, rather than exploiting a single dimension rule-based strategy. To understand how children's allocation of attention may differently affect RB and II learning, it is necessary to examine how the *same* children approach these different category learning tasks.

Further, children's ability to learn RB and II categories has never been compared across modalities. In adults, auditory and visual learning and memory share many similarities (Nahum, Nelken, & Ahissar, 2010; Visscher et al., 2007). In contrast, there is evidence of auditory dominance in children. In unimodal tasks, from infancy until at least 7-8 years old, children show a preference for auditory over visual information, whereas adults show a preference for visual information (Budoff & Quinlan, 1964; Napolitano & Sloutsky, 2004; Robinson & Sloutsky, 2004, 2013; Sloutsky & Napolitano, 2003). Patterns of learning across modalities may change with development. Children's ability to learn temporal adjacencies in the visual modality improves from 5 to 12 years old but learning in the auditory modality stays constant in this same age range (Raviv & Arnon, 2018). These results suggest that younger children may demonstrate better learning for auditory than visual categories.

In all, prior work has demonstrated differences in children and adults in how well and/or how they learn visual RB categories (Huang-Pollock et al., 2011; Rabi & Minda, 2014a; Minda et al., 2008), visual II categories (Huang-Pollock et al., 2011; Rabi & Minda, 2014a; Minda et al., 2008), auditory RB categories (Reetzke et al., 2016), and auditory II categories (Roark & Holt, 2019). However, it is unclear how the same children learn in these different tasks as prior studies have relied on comparison of adults and separate groups of children. There has been very little consideration of how children learn in these different tasks. As a result, little is understood about how the same child learns these different types of categories (RB and II) *and* categories across different modalities (auditory, visual).

In the current study, we investigate learning of rule-based or information-integration auditory and visual categories in 7-12-year-old children. We assess how well participants learn the categories, how well they generalize to novel stimuli without feedback, and the strategies they use during learning.

Methods

Participants completed three sessions – a background assessment session and two category learning sessions.

Participants

Participants were 29 children (10 Female, 19 Male) ages 7-12 years (M = 8.86, SD = 1.46) recruited from participation in previous studies or through a local recruitment database Pitt+Me. All participants received \$10/hour for participation. Families of the children received an additional \$10 for completing all background assessment questionnaires.

Stimuli

We selected pairs of dimensions across modalities that are important for basic perception in both modalities and have been proposed to be analogs of one another (Visscher et al., 2007). Further, we created comparable category distributions that allow for comparison across modalities (Figure 1).

Auditory category stimuli were nonspeech ripple sounds that varied in temporal modulation and spectral modulation. Visual category stimuli were Gabor patches that varied in spatial frequency and orientation. The stimulus distributions were first created in a normalized space and then separately transformed to auditory and visual spaces based on equations used in prior research (Roark et al., 2021). The rule-based (RB) categories can be separated based on a unidimensional rule along the temporal modulation (auditory) and spatial frequency (visual) dimensions. The information-integration (II) categories require both dimensions to separate the categories – a single dimension would lead to suboptimal performance. Each category type had 200 stimuli (100/category). An additional grid of 64 stimuli was presented in the generalization test block.

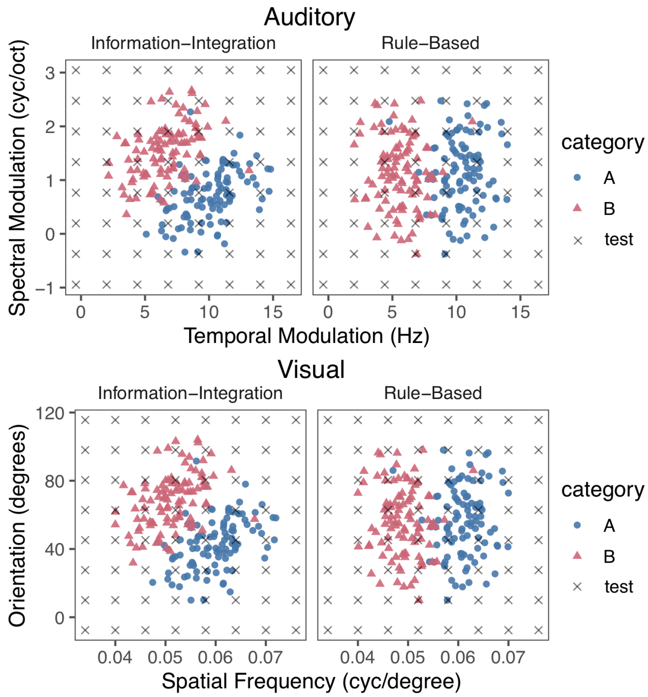

Figure 1: Category distributions.

Procedure

Participants completed one session of assessments of demographics and history of communication or psychological disorders. No children had a communication disorder at the time of testing.

Participants returned at least one week later for a second session. In the second and third sessions (separated by at least one week), they completed four category learning tasks – RB auditory, RB visual, II auditory, and II visual. In each session, participants always completed one auditory and one visual task, counterbalanced in order across participants. This was done to minimize potential carryover effects within a modality. The order of RB and II tasks within modality was also counterbalanced across participants.

To ensure that the task was child-friendly, there was a cover story for each task. For the auditory tasks, participants were told that they were encountering aliens that made different kinds of sounds and needed to decide who was talking. To minimize carryover effects across tasks within the same modality, we oriented participants to different planets in this cover story and used different aliens (blue/red and green/purple) for the RB and II tasks. For the visual tasks, participants were told that they were encountering wizards that had different kinds of crystal balls (inside of which the Gabor patches were presented) and needed to decide which wizard the crystal ball belonged to. We oriented participants to different forest scenes and used different wizards (pink/purple, green/blue) for the RB and II tasks.

Within each category learning task, participants completed four 50-trial blocks of feedback-based training followed by one 64-trial generalization block where they encountered novel exemplars and no longer received any feedback. On each trial, participants heard a sound or saw an image (1 sec), made an untimed response about the category identity (1 or 2 on the keyboard), and received feedback immediately after their response (smiling face icon for Correct and frowning face icon for Incorrect), followed by a 1 sec inter-trial interval. Participants were told to be as accurate as possible and did not receive feedback in the generalization test.

Modeling

To understand the learning strategies that participants used to learn the different categories, we applied decision-bound computational models (Ashby, 1992; Maddox & Ashby, 1993). Specifically, we applied several classes of models to participants' response data that make different assumptions about the types of strategies that participants use – explicit rule-based models, an implicit integration model, and a random responder ("guessing") model. We fit the models to each block of each participant's data to understand their strategy use across tasks and blocks using maximum likelihood estimation (Wickens, 1982). Best-fitting models were decided based on the Bayesian Information Criterion (BIC): BIC = r*ln$N$ - 2ln$L$ where r is the number of free parameters, N is the number of trials in a block for a given subject, and L is the likelihood of the model given the data (Schwarz, 1978). The model with the lowest BIC value was selected as the best-fitting model. The best-fitting models accounted for 66% of participant responses, which is better than chance (50% +/- 12%, 95% cumulative probability).

Rule-based strategies Rule-based strategies involve selective attention to individual dimensions. We fit separate models that assume that participants used a rule-based strategy along the two available dimensions. The two dimensions in the auditory modality were temporal and spectral modulation and in the visual modality were spatial frequency and orientation. One example strategy in an auditory task might be to categorize all stimuli with a temporal modulation rate faster than 8 Hz into Category A and all stimuli with a rate slower than 8 Hz into Category B. Rule-based models each have two free parameters – the location of a decision boundary along the dimension and a perceptual/criterial noise parameter. The optimal strategy is a rule along temporal modulation for auditory-RB categories and a rule along spatial frequency for visual-RB categories.

Integration strategies Integration strategies involve integration across both stimulus dimensions to separate the categories. Integration strategies are thought to reflect implicit, procedural learning processes with boundaries that are not easy for participants to verbalize (Ashby et al., 1998). The integration model assumes that participants separate the categories with a linear decision boundary and has three free parameters: the slope and intercept of the decision boundary and a perceptual/criterial noise parameter. An integration strategy that has a positive slope is optimal for the auditory-II and visual-II categories.

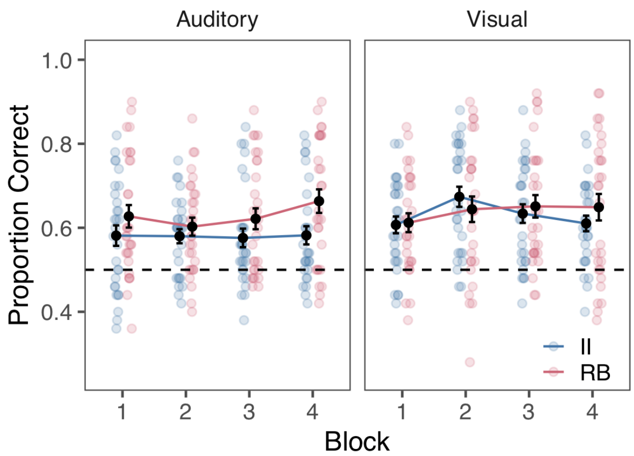

Figure 2: Category learning accuracy across blocks in the four different tasks. Individual subject performance is shown in colored dots. Error bars reflect *SEM.*

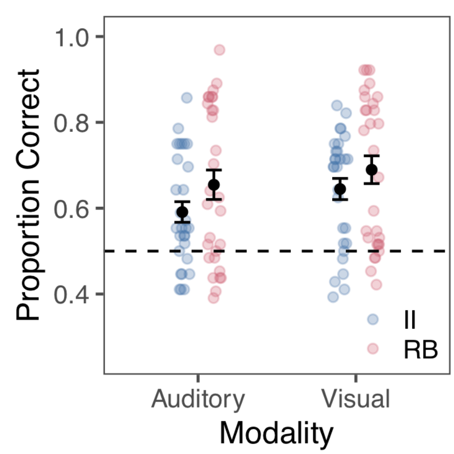

Figure 3: Generalization test accuracy. Individual subject performance is shown in colored dots. Error bars reflect *SEM.*

Random responder/guessing strategies We fit a random responder model that assumes that a participant guesses on each trial. This enables examination of behavior when participants do not have a clear idea of the category identities.

Results

To understand how children learn auditory and visual RB and II categories, we compared their performance during learning, their performance during generalization, and their learning strategies across the tasks.

Category learning

Children learned the different categories to differing degrees of success (Figure 2). We ran a repeated measures ANOVA with modality (auditory/visual), category (RB/II), and block (1-4) as factors.

Overall, accuracy was significantly higher in the visual tasks than the auditory tasks ($F(1, 28) = 4.24$, $p = .049$, $\eta_g^2 = .014$). However, there was also a significant interaction between modality and performance across blocks ($F(2.12, 59.5) = 4.91$, $p = .009$, $\eta_g^2 = .010$). Bonferroni-corrected post-hoc tests indicated that visual tasks had significantly higher accuracy than auditory tasks in blocks 2 ($p = .001$, visual: 66%, auditory: 59%) and 3 ($p = .020$, visual: 64%, auditory: 60%). There were no significant differences across modalities in blocks 1 ($p = .80$, visual: 61%, auditory: 60%) or 4 ($p = .71$, visual: 63%, auditory: 62%).

Though there were no significant differences between average RB and II accuracy ($F(1, 28) = 3.33$, $p = .079$, $\eta_g^2 = .012$), there was a significant interaction between the category being learned and performance across blocks ($F(3, 84) = 2.87$, $p = .041$, $\eta_g^2 = .0080$). Bonferroni-corrected post-hoc tests indicated that there were no significant differences between RB and II accuracy in blocks 1, 2, and 3 (*ps* > .12), but accuracy was significantly higher in the RB task than the II task in block 4 ($p = .005$, RB: 66%, II: 60%).

Performance was stable across most of the task, with most learning gains occurring in the first block. There were no significant differences across blocks ($F(2.19, 61.4) = 1.47$, $p = .24$, $\eta_g^2 = .004$). No other main effects or interactions were significant (*ps* > .17).

These results indicate that children learn these carefully matched RB and II categories differently, but only in the final block. Further, this pattern was similar across the auditory and visual modalities, indicating that category learning may be supported by modality-general mechanisms.

However, children also performed better in the visual tasks than the auditory tasks in the middle blocks of learning. In the first and final blocks, there were no significant differences between the modalities. This may indicate that participants were able to glean something about the visual stimuli more rapidly than the auditory stimuli, boosting their performance in those intermediate blocks. However, with more experience, they were able to end the tasks with similar performance across modalities.

Generalization

In the generalization test, we tested participants on a grid of stimuli to see how well they were able to generalize to stimuli that fell in trained and untrained regions of space (Figure 1).

We examined the differences between children's ability to apply previously learned categorization knowledge to these novel exemplars. We excluded any stimuli from this grid that fell directly between the two categories (i.e., did not clearly belong to one category or another). We then calculated the accuracy based on how well responses matched the ground-truth category identity of the generalization test stimuli.

Children's ability to generalize their categorization knowledge to novel exemplars differed based on the category they were learning ($F(1, 28) = 4.61$, $p = .041$, $\eta_g^2 = .030$) and the modality of the stimuli ($F(1, 38) = 5.13$, $p = .031$, $\eta_g^2 = .020$). Specifically, children had higher generalization accuracy for RB (67%) than II categories (62%; 95% CI [1.15, 9.69]) and for visual ($M = 67\%$) than auditory tasks (*M*

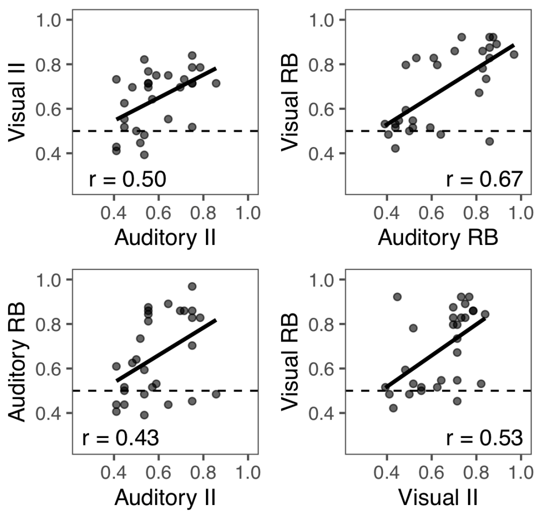

Figure 4: Correlations between test performance in tasks with the same category in different modalities (top) and same modality with different categories (bottom).

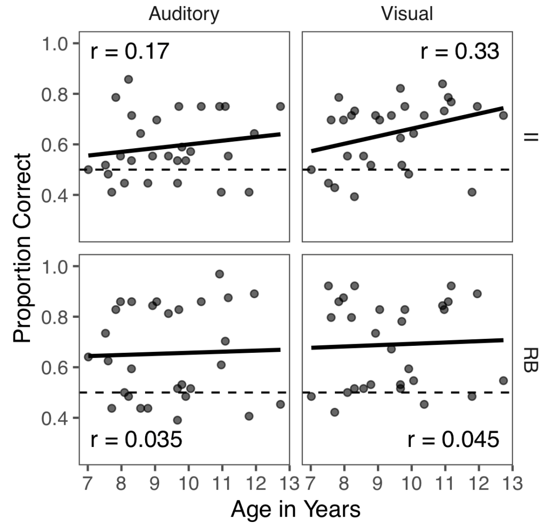

Figure 5: Generalization test accuracy by age in the children group.

= 62%; 95% CI [.80, 8.06]). There was no significant interaction between category and modality ($F(1, 28) = 0.30$, $p = .59$, $\eta_g^2 = .00090$).

A key component of the current study is that we examined learning across these four tasks in the *same* individuals. This provides the ability to understand how the same child learned across these diverse tasks. To better understand how the same individuals learned these different categories, we examined the correlation between generalization performance across tasks (Figure 4). Generalization test performance was significantly positively correlated in the II tasks in the auditory and visual modalities ($r = 0.50$, $p = .0056$), the RB tasks in the auditory and visual modalities ($r = 0.67$, $p < .001$), the II and RB tasks in the auditory modality ($r = 0.43$, $p = .020$), and the II and RB tasks in the visual modality ($r = 0.53$, $p = .0028$). We compared the strengths of the correlations across tasks using the *cocor* package in R (Diedenhofen & Musch, 2015). There were no significant differences in the correlations between the II auditory-visual ($r = 0.50$) and RB auditory-visual tasks ($r = 0.67$; $p = .32$) or between the auditory II-RB ($r = 0.43$) and visual II-RB tasks ($r = 0.53$; $p = .57$). This indicates that the ability to learn and generalize knowledge about these categories is related across tasks regardless of modality or the type of category being learned.

It is also important to note that the children in this study had ages across a relatively wide developmental timespan (e.g., 7-12 years). To better understand how these age differences might relate to their performance in these four tasks, we examined the correlation between age (in decimal years based on date of the experiment and their birthday) and accuracy in the generalization test (Figure 5). There was no significant correlation in any task (*ps* > .07) and there were no significant differences among the correlations (*ps* > .11), assessed with *cocor* package in R.

Together, these results indicate that perceptual category learning in children may be supported by category- and modality-general abilities. Overall, children were somewhat more successful at learning and generalizing their knowledge about visual categories, regardless of category type, and RB categories, regardless of modality.

Learning strategies

Accuracy alone does not provide detailed information about *how* participants learn these categories. To better understand how learners approached these categorization problems, we examined their learning strategies using decision-bound computational models (Figure 6).

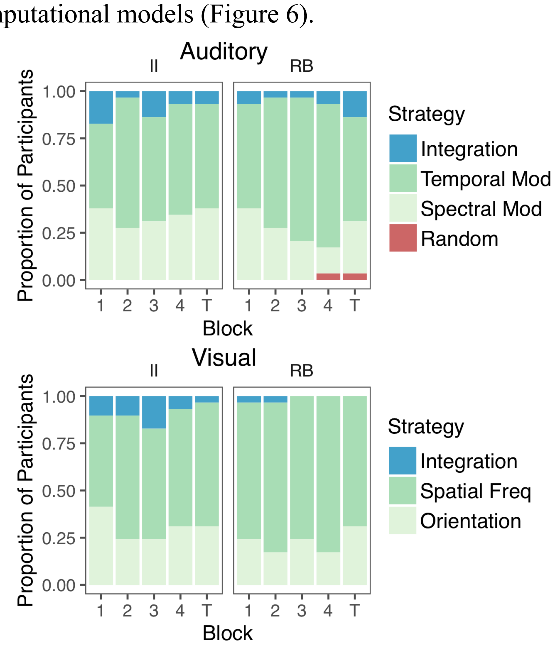

Figure 6: Learning strategies across blocks and in the generalization test for the auditory and visual tasks.

Participants overwhelming used rule-based strategies across tasks, regardless of whether this was optimal for the task. Even by the final block of learning, in both the auditory and visual II tasks, 93% of participants used suboptimal rule-based strategies, compared to only 7% using the optimal integration strategy. In the auditory-II task, 59% used temporal modulation strategies and 34% used spectral modulation strategies. In the visual-II task, 62% used spatial frequency strategies and 31% used orientation strategies.

In the RB tasks, rule-based strategies are the optimal strategies for learning. That is, participants could maximize their accuracy if they selectively attended to the temporal modulation dimension in the auditory-RB task or the spatial frequency dimension in the visual-RB task. In contrast to the II tasks, many participants used the optimal strategies during the RB tasks. In fact, the optimal rule-based strategies were the most common strategies in every block. By the final block of learning, 76% of participants in the auditory-RB task and 83% of participants in the visual-RB task used the optimal rule-based strategy to separate the categories.

Discussion

We investigated rule-based and information-integration auditory and visual perceptual category learning in 7-12-year-old children. We found that learning was strongly correlated across tasks and modalities, indicating a potential source of learning ability that is both category- and modality-general. We also found that children overwhelmingly used rule-based strategies to solve these categorization problems, regardless of whether it was optimal for the task at hand. Relatedly, children also learned and generalized to RB categories better than II categories. These results provide substantial insights into the nature of perceptual category learning in children.

Prior work has focused on category learning in either the visual or auditory modalities. Our work expands the literature by directly investigating visual and auditory learning in the same individuals. Rather than a bias for learning in the auditory modality, as has been demonstrated with problems other than category learning (Budoff & Quinlan, 1964; Raviv & Arnon, 2018), we found that children sometimes performed better in the visual modality. Additionally, the ability to learn either visual or auditory categories did not differ by age across our 7- to 12-year-old sample. These results suggest that the processes children use to learn categories may be somewhat more beneficial for the visual modality and may not depend on mechanisms that mature in this age range.

However, we also found that children's ability to learn these categories was strongly correlated across tasks. Recent work in adults has also found category learning is strongly correlated across modalities (Roark et al., 2021). These results suggest that perceptual category learning abilities in children may be supported by both category- and modality-general mechanisms.

We found that by the end of learning and in the generalization test, children demonstrated a consistent advantage for learning RB over II categories. One potential factor to this RB advantage is that children overwhelmingly used rule-based strategies across tasks. That is, children used strategies based on selective attention, even when that was not optimal for learning.

At face value, the bias towards rule-based strategies seems to conflict with work that shows that children are more likely to integrate across dimensions, rather than selectively attend to them. However, much of this developmental trajectory is thought to occur between the ages of 5 and 8 (Kemler & Smith, 1978; Smith & Kemler, 1978), at the early end of our sample here. Our findings are consistent with prior work that shows that children tend to perseverate with suboptimal rule-based strategies in both RB and II tasks (Huang-Pollock et al., 2011; Rabi & Minda, 2014a; Rabi et al., 2015; Roark & Holt, 2019). Our results suggest that the bias to use unidimensional rules in children is independent of the modality of the stimuli.

The finding that children were also better able to generalize to RB categories than II categories is consistent with the adult literature. The generalization stimuli that we used included stimuli that fell within the trained category regions and stimuli in untrained regions. In adults, generalization is more robust for RB categories than II categories, especially in untrained regions of space (Casale, Roeder, & Ashby, 2012; Smith et al., 2015). While RB categories can be learned using rules that apply unambiguously to untrained regions of space, learning of II categories relies on learning stimulus-response associations that are specific to the training set. As a result, learning stimulus-response associations limits generalization. Though children primarily used rule-based strategies, our results suggest that children show a similar pattern of generalization as adults and that RB generalization is more robust than II generalization.

Further, we observed that there was variability across this sample of children in their ability to learn each of these four categories. Recent work suggests that adults are also quite variable in their category learning ability (Llanos et al., 2020; Roark & Chandrasekaran, 2021; Shamloo & Hélie, 2020; Shen & Palmeri, 2016). Much is still not understood about what drives individual differences in learning performance in adults, but a key factor may be working memory ability (Craig & Lewandowsky, 2011; Lewandowsky et al., 2012; Lloyd et al., 2019; McHaney et al., 2021; Roark & Chandrasekaran, 2021). Future work should focus on the factors driving individual differences in children's learning and whether these are the same or different across modalities. Additional longitudinal work could also reveal how individual differences in learning in childhood might relate to individual differences in learning in adulthood.

In all, our results suggest that perceptual category learning in children may involve category- and modality-general mechanisms, with substantial individual differences across children. Further, instead of being better able to integrate across dimensions, children showed a bias to use unidimensional rules regardless of whether it was helpful for categorization. These results have implications for understanding the development of category learning and individual differences in cognition during development.

Acknowledgments

This research was supported by the National Institute on Deafness and Other Communication Disorders (F32DC018979 to C.L.R. and R21DC017227 to A.H.W.).

References

Ashby, F. G. (1992). *Multidimensional models of categorization* (F. G. Ashby, Ed.; pp. 449–483). Lawrence Erlbaum.

Ashby, F. G., Alfonso-Reese, L. A., Turken, A. U., & Waldron, E. M. (1998). A neuropsychological theory of multiple systems in category learning. *Psychological Review*, *105*(3), 442–481.

Ashby, F. G., & Maddox, W. T. (2011). Human category learning 2.0. *Annals of the New York Academy of Sciences*, *1224*, 147–161.

Blanco, N. J., & Sloutsky, V. M. (2019). Adaptive Flexibility in Category Learning? Young Children Exhibit Smaller Costs of Selective Attention Than Adults. *Developmental Psychology*, *October*.

Blanco, N. J., & Sloutsky, V. M. (2020). Attentional mechanisms drive systematic exploration in young children. *Cognition*, *202*, 104327.

Budoff, M., & Quinlan, D. (1964). Auditory and Visual Learning in Primary Grade Children. *Child Development*, *35*(3), 583–586.

Casale, M. B., Roeder, J. L., & Ashby, F. G. (2012). Analogical transfer in perceptual categorization. *Memory & Cognition*, *40*(3), 434–449.

Casey, B. J., Davidson, M. C., Hara, Y., Thomas, K. M., Martinez, A., Galvan, A., Halperin, J. M., Rodríguez-Aranda, C. E., & Tottenham, N. (2004). Early development of subcortical regions involved in non-cued attention switching. *Developmental Science*, *7*(5), 534–542.

Cowan, N. (2016). Working Memory Maturation. *Perspectives on Psychological Science*, *11*(2), 239–264.

Craig, S., & Lewandowsky, S. (2011). Whichever way you Choose to Categorize, Working Memory Helps you Learn. *Quarterly Journal of Experimental Psychology*, *65*(3), 439–464.

Deng, W. (Sophia), & Sloutsky, V. M. (2016). Selective attention, diffused attention, and the development of categorization. *Cognitive Psychology*, *91*, 24–62.

Diamond, A. (2002). *Normal Development of Prefrontal Cortex from Birth to Young Adulthood: Cognitive Functions, Anatomy, and Biochemistry* (Stags & Knight, Eds.; pp. 466–503).

Diedenhofen, B., & Musch, J. (2015). cocor: A Comprehensive Solution for the Statistical Comparison of Correlations. *PLOS ONE*, *10*(4), e0121945.

Gathercole, S. E. (1999). Cognitive approaches to the development of short-term memory. *Trends in Cognitive Sciences*, *3*(11), 410–419.

Gogtay, N., Giedd, J. N., Lusk, L., Hayashi, K. M., Greenstein, D., Vaituzis, A. C., Nugent, T. F., Herman, D. H., Clasen, L. S., Toga, A. W., Rapoport, J. L., & Thompson, P. M. (2004). Dynamic mapping of human cortical development during childhood through early adulthood. *Proceedings of the National Academy of Sciences of the United States of America*, *101*(21), 8174–8179.

Hazan, V., & Barrett, S. (2000). The development of phonemic categorization in children aged 6-12. *Journal of Phonetics*, *28*(4), 377–396.

Holt, L. L., & Lotto, A. J. (2010). Speech perception as categorization. *Attention, Perception, & Psychophysics*, *72*(5), 1218–1227.

Huang-Pollock, C. L., Maddox, W. T., & Karalunas, S. L. (2011). Development of implicit and explicit category learning. *Journal of Experimental Child Psychology*, *109*(3), 321–335.

Idemaru, K., & Holt, L. L. (2013). The developmental trajectory of children's perception and production of English /r/-/l/. *The Journal of the Acoustical Society of America*, *133*(6), 4232–4246.

Kemler, D. G., & Smith, L. B. (1978). Is there a developmental trend from integrality to separability in perception? *Journal of Experimental Child Psychology*, *26*(3), 498–507.

Kolk, S. M., & Rakic, P. (2021). Development of prefrontal cortex. *Neuropsychopharmacology*, *47*(1), 1–17.

Lewandowsky, S., Yang, L.-X., Newell, B. R., & Kalish, M. L. (2012). Working memory does not dissociate between different perceptual categorization tasks. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *38*(4), 881–904.

Liquin, E. G., & Gopnik, A. (2022). Children are more exploratory and learn more than adults in an approach-avoid task. *Cognition*, *218*, 104940.

Llanos, F., McHaney, J. R., Schuerman, W. L., Yi, H. G., Leonard, M. K., & Chandrasekaran, B. (2020). Non-invasive peripheral nerve stimulation selectively enhances speech category learning in adults. *Npj Science of Learning*, *5*(1), 12.

Lloyd, K., Sanborn, A., Leslie, D., & Lewandowsky, S. (2019). Why Higher Working Memory Capacity May Help You Learn: Sampling, Search, and Degrees of Approximation. *Cognitive Science*, *43*(12), e12805.

Lucas, C. G., Bridgers, S., Griffiths, T. L., & Gopnik, A. (2014). When children are better (or at least more open-minded) learners than adults: Developmental differences in learning the forms of causal relationships. *Cognition*, *131*(2), 284–299.

Maddox, W. T., & Ashby, F. G. (1993). Comparing decision bound and exemplar models of categorization. *Perception & Psychophysics*, *53*(1), 49–70.

McHaney, J. R., Tessmer, R., Roark, C. L., & Chandrasekaran, B. (2021). Working memory relates to individual differences in speech category learning: Insights from computational modeling and pupillometry. *Brain and Language*, *222*, 105010.

Minda, J. P., Desroches, A. S., & Church, B. A. (2008). Learning rule-described and non-rule-described categories: a comparison of children and adults. *Journal of*

Experimental Psychology: Learning, Memory, and Cognition, *34*(6), 1518–1533.
Minda, J. P., & Miles, S. J. (2009). Learning new categories: Adults tend to use rules while children sometimes rely on family resemblance. *Proceedings of the 31th Annual Conference of the Cognitive Science Society*, 1518–1523.
Nahum, M., Nelken, I., & Ahissar, M. (2010). Stimulus uncertainty and perceptual learning: Similar principles govern auditory and visual learning. *Vision Research*, *50*(4), 391–401.
Napolitano, A. C., & Sloutsky, V. M. (2004). Is a picture worth a thousand words? The flexible nature of modality dominance in young children. *Child Development*, *75*(6), 1850–1870.
Nittrouer, S. (2004). The role of temporal and dynamic signal components in the perception of syllable-final stop voicing by children and adults. *Journal of the Acoustical Society of America*, *115*(4), 1777–1790.
Nittrouer, S., Manning, C., & Meyer, C. (1993). The perceptal weighting of acoustic cues changes with linguistic experience. *Proceedings of the Acoustical Society of America*, *94*(3), 1865–1865.
Plebanek, D. J., & Sloutsky, V. M. (2017). Costs of Selective Attention: When Children Notice What Adults Miss. *Psychological Science*, 095679761769300–095679761769300.
Plude, D. J., Enns, J. T., & Brodeur, D. (1994). The development of selective attention: A life-span overview. *Acta Psychologica*, *86*(2–3), 227–272.
Rabi, R., Miles, S. J., & Minda, J. P. (2015). Learning categories via rules and similarity: Comparing adults and children. *Journal of Experimental Child Psychology*, *131*, 149–169.
Rabi, R., & Minda, J. P. (2014a). Perceptual Category Learning: Similarity and Differences Between Children and Adults. *Proceedings of the 36th Annual Conference of the Cognitive Science Society (pp.* 2811–2816). Cognitive Science Society.
Rabi, R., & Minda, J. P. (2014b). Rule-Based Category Learning in Children: The Role of Age and Executive Functioning. *PLoS ONE*, *9*(1), e85316.
Raviv, L., & Arnon, I. (2018). The developmental trajectory of children's auditory and visual statistical learning abilities: modality-based differences in the effect of age. *Developmental Science*, *21*(4), e12593.
Reetzke, R., Maddox, W. T., & Chandrasekaran, B. (2016). The role of age and executive function in auditory category learning. *Journal of Experimental Child Psychology*, *142*, 48–65.
Richler, J. J., & Palmeri, T. J. (2014). Visual category learning. *Wiley Interdisciplinary Reviews: Cognitive Science*, *5*(1), 75–94.
Roark, C. L., & Chandrasekaran, B. (2021). Individual variability in strategies and learning outcomes in auditory category learning. In T. Fitch, C. Lamm, H. Leder, & K. Tessmar (Eds.), *Proceedings of the 43rd Annual Conference of the Cognitive Science Society* (pp. 154–160). Cognitive Science Society.
Roark, C. L., & Holt, L. L. (2019). Auditory information-integration category learning in young children and adults. *Journal of Experimental Child Psychology*, *188*, 104673.
Roark, C. L., Paulon, G., Sarkar, A., & Chandrasekaran, B. (2021). Comparing perceptual category learning across modalities in the same individuals. *Psychonomic Bulletin & Review*, *28*(3), 898–909.
Robinson, C. W., & Sloutsky, V. M. (2004). Auditory Dominance and Its Change in the Course of Development. *Child Development*, *75*(5), 1387–1401.
Robinson, C. W., & Sloutsky, V. M. (2013). When audition dominates vision: evidence from cross-modal statistical learning. *Experimental Psychology*, *60*(2), 113–121.
Schwarz, G. (1978). Estimating the Dimension of a Model. *The Annals of Statistics*, *6*(2), 461–464.
Shamloo, F., & Hélie, S. (2020). A study of individual differences in categorization with redundancy. *Journal of Mathematical Psychology*, *99*, 102467.
Shen, J., & Palmeri, T. J. (2016). Modelling individual difference in visual categorization. *Visual Cognition*, *24*(3), 260–283.
Sloutsky, V. M., & Fisher, A. V. (2004). When Development and Learning Decrease Memory. *Psychological Science*, *15*(8), 553–558.
Sloutsky, V. M., & Napolitano, A. C. (2003). Is a picture worth a thousand words? Preference for auditory modality in young children. *Child Development*, *74*(3), 822–833.
Smith, J. D., Zakrzewski, A. C., Johnston, J. J. R., Roeder, J. L., Ashby, F. G., & Church, B. A. (2015). Generalization of Category Knowledge and Dimensional Categorization in Humans (Homo sapiens) and Nonhuman Primates (Macaca mulatta). *Journal of Experimental Psychology: Animal Learning and Cognition*, *41*(4): 322-335.
Smith, L. B., & Kemler, D. G. (1978). Levels of experienced dimensionality in children and adults. *Cognitive Psychology*, *10*(4), 502–532.
Visscher, K. M., Kaplan, E., Kahana, M. J., & Sekuler, R. (2007). Auditory Short-Term Memory Behaves Like Visual Short-Term Memory. *PLoS Biology*, *5*(3), e56.
Wickens, T. D. (1982). *Models for Behavior: Stochastic Processes in Psychology*. W. H. Freeman.
Zevin, J. D. (2012). A sensitive period for shibboleths: The long tail and changing goals of speech perception over the course of development. *Developmental Psychobiology*, *54*(6), 632–642.