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Auditory information-integration category learning in young children and adults

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ABSTRACT

Adults outperform children on category learning that requires selective attention to individual dimensions (rule-based categories) due to their more highly developed working memory abilities, but much less is known about developmental differences in learning categories that require integration across multiple dimensions (information-integration categories). The current study investigated auditory information-integration category learning in 5- to 7-year-old children ($n = 34$) and 18- to 25-year-old adults ($n = 35$). Adults generally outperformed children during learning. However, some children learned the categories well and used strategies similar to those of adults, as assessed through decision-bound computational models. The results demonstrate that information-integration learning ability continues to develop throughout at least middle childhood. These results have implications for the development of mechanisms that contribute to speech category learning.

Introduction

Children demonstrate a remarkable ability to learn complex auditory categories, as illustrated by their acquisition of the complex speech categories of a native language. Within the first year of life, infants' experience in a language community leads them to better distinguish phonetic categories

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from within the native language and to more poorly distinguish nonnative categories that do not align with the native language (Kuhl et al., 2006; Werker & Tees, 1984). This is thought to be a result of native-language speech category learning and the warping of perceptual space that accompanies it. This category learning continues throughout childhood, with phonetic categorization not fully adult-like until after at least 12 years of age (Idemaru & Holt, 2013; Nittrouer, 2004; Nittrouer, Manning, & Meyer, 1993; Zevin, 2012). Although it is clear that auditory categories continue to develop across childhood, very little is known about the developmental course of the learning mechanisms available to support such category learning.

Part of the reason for this is that it is impossible to control and manipulate children's history of speech experience. For this reason, auditory category learning across artificial nonspeech categories can be a useful tool to reveal learning mechanisms available to conquer the important challenge of native-language speech category learning. In the current study, we investigated young (5- to 7-year-old) children's nonspeech *information-integration* (II) auditory category learning, a learning challenge that has been compared to the demands of speech category learning, with targeted hypotheses developed from an influential model of adult category learning (Chandrasekaran, Koslov, & Maddox, 2014).

Dual category learning systems

One well-studied model for understanding category learning, the competition between verbal and implicit systems (COVIS) model (Ashby, Alfonso-Reese, Turken, & Waldron, 1998), implicates at least two systems involved in category learning. Although primarily developed to account for adult visual category learning, the COVIS model recently has been expanded to auditory and speech category learning (Chandrasekaran, Koslov, et al., 2014; Chandrasekaran, Yi, & Maddox, 2014). To better understand the mechanisms that give rise to complex communication and speech perception, it is necessary to illuminate the cognitive processes involved in auditory category learning and to observe how these differ in children and adults.

The dual systems of the COVIS model are the explicit (reflective) and implicit (reflexive) systems. A large literature makes the case that the nature of the distributions of exemplars that define categories is important in determining which system is optimal for learning (for review, see Ashby & Maddox, 2011). When exemplars are sampled such that the optimal boundary distinguishing categories can be defined by a simple verbalizable rule across input dimensions that can be attended to selectively, the explicit system is advantaged in learning. Such *rule-based* categories are thought to be optimally learned through the explicit system and to involve selective attention and working memory processes mediated, at least in part, via involvement of the prefrontal cortex (PFC) (Ashby et al., 1998; Nomura et al., 2007). Another component of the explicit system, the head of the striatum's caudate nucleus, is thought to be involved in feedback processing and switching among rules (Filoteo et al., 2005; Tricomi & Fiez, 2008). Thus, through hypothesis generation, rule selection and application, and switching among rules during learning, the explicit system is well matched to drive responses for rule-based category learning tasks that require selective attention to the individual dimensions defining category exemplars.

In contrast, an implicit procedural learning system is thought to dominate learning when category exemplars are defined by distributions that require integration across multiple dimensions—such that no single dimension can uniquely determine category membership (Ashby & Maddox, 2011). According to the dual systems approach implemented in the COVIS model, such II categories are optimally learned through procedural learning mechanisms of an implicit system (Ashby, Ell, & Waldron, 2003) that involves the body and tail of the caudate nucleus in the striatum (Filoteo & Maddox, 2007; Nomura et al., 2007). Moreover, because speech categories are highly multidimensional and not typically distinguished by single acoustic dimensions (Holt & Lotto, 2006), a case can be made for the involvement of the implicit system in speech category acquisition (Chandrasekaran, Koslov, et al., 2014; Yi, Maddox, Mumford, & Chandrasekaran, 2016).

The explicit system and implicit system are thought to be distinct and to compete during learning (Ashby et al., 1998). The explicit system is thought to be the default system that initially drives responses among adult learners. With additional training or experience through feedback, responses shift from being driven by the explicit system to being driven by the implicit system when the structure of the categories demands it (Ashby et al., 1998). This competitive dynamic is inferred from results demonstrating that unidimensional rule-based strategies tend to dominate early learning, even when integration strategies are optimal for the categorization challenge (Ashby & Crossley, 2010; Ashby & Maddox, 2011; Ashby, Queller, & Berretty, 1999). When the categories to be learned are II categories, rule-based strategies do not lead to success and feedback gradually pushes the implicit system to drive responses and motor system output (Ashby & Maddox, 2011; Ashby et al., 1998). The initial involvement of the explicit system is beneficial for rule-based category learning, which therefore typically proceeds more quickly than II category learning (Ashby & Maddox, 2011). For II categories there is a delay in engaging the optimal implicit learning system and thus learning is slower, with optimal strategies emerging later in learning (Ashby & Maddox, 2011).

The brain regions involved in the dual learning systems model undergo distinct patterns of development. The striatally mediated implicit category learning system matures earlier than the explicit system. The caudate nucleus matures early in development and is thought to be fully adult-like by 7 years of age (Casey et al., 2004). More generally, procedural memory and learning systems are thought to be fully adult-like by about 10 years of age, in contrast to the protracted developmental course of declarative memory systems involved in the explicit system such as the PFC and medial temporal lobe (Diamond, 2002; Finn et al., 2016).

The COVIS model depicts the implicit system as independent from the developmentally sensitive working memory abilities that it posits to influence categorization via the explicit system (Ashby & Maddox, 2011; Ashby et al., 1998). Instead, the implicit system is thought to build up category representations as procedurally learned stimulus–response associations acquired over the course of experience rather than via hypothesis testing. Thus, within the COVIS model, the striatally mediated implicit system is predicted to operate independently from involvement of PFC development and from developmental constraints on working memory capacity.

This independence from working memory abilities might suggest the possibility that children may learn II categories similarly to adults, in contrast to the protracted development of rule-based category learning (Reetzke, Maddox, & Chandrasekaran, 2016). Yet, despite this prediction, a study of visual II category learning in 8- to 12-year-old children found that although many children were able to optimally integrate across the dimensions during learning, adults outperformed children overall (Huang-Pollock, Maddox, & Karalunas, 2011). The authors argued that children's poorer II category learning relative to adults may have been due to the developmentally immature PFC's involvement in switching control from early involvement of the explicit system in the learning task (as posited by the COVIS model; Ashby et al., 1998) to the implicit system. However, 8- to 12-year-old children are arguably fairly far along the trajectory of PFC development. From this single study, it remains unclear whether younger children, who have less well-developed working memory and switching abilities, may approach II category learning differently than either adults or older children, as examined in previous studies.

Aside from this single developmental study, several other areas of research have investigated the role of working memory in II category learning by taxing working memory resources during learning or investigating individual differences in working memory capacity in adults. However, this empirical literature reveals a lack of consensus about the involvement of working memory in II category learning. Whereas some studies have shown that there is no effect of increasing working memory demands on II category learning in adults (Maddox, Ashby, Ing, & Pickering, 2004; Maddox, Filoteo, Hejl, & Ing, 2004; Miles & Minda, 2011; Waldron & Ashby, 2001; Zeithamova & Maddox, 2007), other studies have reported that II category learning can actually be *facilitated* by increased working memory demand (Filoteo, Lauritzen, & Maddox, 2010; but see Newell, Moore, Wills, & Milton, 2013). Yet other studies have found II category learning to be *impaired* by increased working memory demand (Miles, Matsuki, & Minda, 2014; Zeithamova & Maddox, 2006; but see Newell, Dunn, & Kalish, 2010).

It may be possible to resolve these seemingly contradictory effects in the literature through a developmental perspective regarding the nature of the shift of control from the explicit system to the implicit system. Several hypotheses about the nature of the interaction between the explicit and implicit systems can be proposed and tested by examining II category learning in young children and adults.

One hypothesis is that lower working memory resources may improve II category learning in some circumstances, perhaps by *hastening* the shift in control from the explicit system to the implicit system. By this hypothesis, young children should outperform adults in II category learning because the explicit system quickly taxes the available working memory resources and becomes less efficient, allowing the implicit system to drive responses earlier in learning. Thus, young children would show better performance than adults and a propensity to shift toward optimal integration strategies early in learning as the implicit system takes control.

An alternative hypothesis is that lower working memory resources may diminish II category learning by *preventing* the shift in control from the explicit system to the implicit system. With this hypothesis, young children should perform worse than adults in II category learning because there are not enough resources to shift the control between systems. This hypothesis suggests that the switch from the explicit system to the implicit system may involve working memory or other developmentally sensitive abilities. Thus, young children would show worse performance than adults and demonstrate an overreliance on suboptimal rule-based strategies because there is a failure in the shift from the explicit system to the implicit system. This impairment hypothesis is also consistent with a single system approach, whereby category learning occurs under a single system sensitive to working memory demands (Kalish, Newell, & Dunn, 2017; Lewandowsky, Yang, Newell, & Kalish, 2012; Newell, Dunn, & Kalish, 2011). From a single system perspective, better working memory capacity and a better developed PFC should lead adults to outperform children in II category learning.

A third hypothesis is that lower working memory capacity will have no effect on II learning because the implicit system itself and the shift between the explicit and implicit systems are independent from working memory abilities and involvement of the PFC. With this hypothesis, young children and adults should learn II categories equivalently and demonstrate similar strategy patterns during learning.

These three opposing hypotheses center on the involvement of an explicit system and an implicit system in learning—a core tenant of the COVIS model. Because the current formulation of the COVIS model does not expand on the precise mechanism of the shift between these two systems during learning and whether working memory is involved or not, these opposing predictions are all generally consistent with the COVIS model. As a result, there is the need for empirical data that may help to resolve these theoretical ambiguities. In this spirit, the current study investigated the potential role of working memory in the shift between the learning systems more directly than previous research.

The current study extended prior developmental research on II category learning to a younger age group and into the auditory modality to understand the differences in performance and strategies in young children and adults. It also tested competing hypotheses regarding the involvement of working memory in II category learning that arise from contrasting findings in the prior literature to understand how the explicit and implicit systems might interact to influence learning at distinct stages of development. Because there have been no studies of *auditory* II category learning to inform the mechanisms that may be available to children to support the extended development of speech categories through childhood, it would be theoretically revealing to examine II category learning in young children.

We examined auditory II category learning in 5- to 7-year-old children and adults. We estimated decision strategies at play across category learning using decision-bound computational models to monitor the shift from the explicit system to the implicit system. Finally, we measured verbal working memory capacity as a measure of reliance on the explicit system and to observe how individual differences in working memory capacity might relate to performance (Zeithamova & Maddox, 2007).

Method

Participants

Participants were 34 children aged 5–7 years (M = 6.56 years, range = 5.25–7.98) recruited from schools and day camps in the Pittsburgh area in the eastern United States and 35 adults aged 18–25 years (M = 20.47 years, range = 18.02–25.34) recruited from the Carnegie Mellon University community. The children received a small gift for participating, and the adults received partial course credit or a small payment ($10) for participating. Four children were excluded from analyses due to a computer error that prevented them from completing testing. One adult was excluded from analyses on the basis of identification as an outlier in posttest performance (more than 3 standard deviations below the adult performance mean). As such, 30 children (M = 6.66 years, range = 5.42–7.98) and 34 adults (M = 20.3 years, range = 18.0–23.0) were included in the final analyses. We collected birthdate and recorded day of testing information to calculate each participant's age in decimal years.

Stimuli

The category distributions from which stimulus exemplars were drawn were defined based on two Gaussian distributions along two acoustic dimensions. The distributions were arranged in the space to form two categories requiring pre-decisional integration across the two acoustic dimensions. Each category had 100 stimulus exemplars, as shown in Fig. 1. The category exemplars were complex tones defined in an acoustic space according to center frequency (CF) and modulation frequency (MF). Each stimulus was created from a sine wave tone with a particular CF modulated with a depth of 100 Hz at the corresponding MF, depending on the exemplar's position in the stimulus distribution. Each stimulus was 300 ms long, sampled at 10 kHz with a 16-bit resolution, and root mean squared matched in amplitude. We chose these particular stimulus dimensions because the dimensions have been used in previous studies of adult auditory category learning (Holt & Lotto, 2006; Roark & Holt, 2018).

Procedure

Category learning and generalization

Participants first completed four 48-trial training blocks, after which they completed a 50-trial generalization posttest. Half of the exemplars from each category were presented during training; the other half were reserved for the generalization test so that no posttest stimulus was encountered during training.

On each training trial, participants saw two alien cartoon characters on a computer screen, one red and one blue, with left/right placement counterbalanced across participants. Participants were

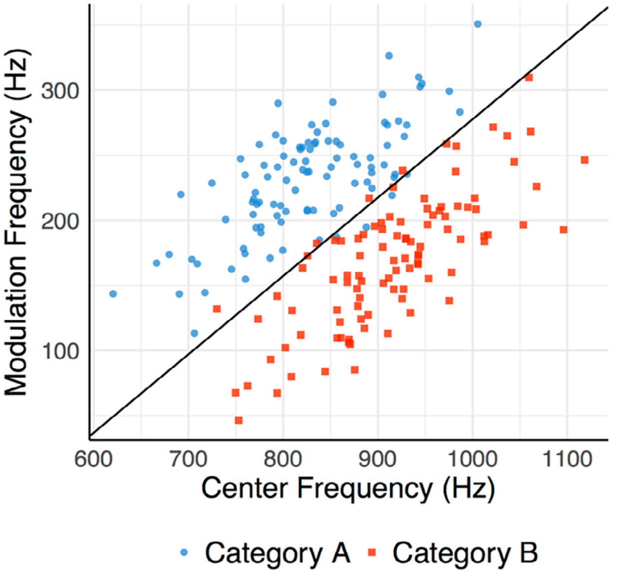

Fig. 1. Information-integration stimulus distributions defined across center frequency and modulation frequency. The solid line represents the optimal boundary between the categories.

informed that they would hear a sound on each trial and that they would need to choose which alien made the sound and press a key (*u* or *i* on a keyboard) to indicate their choice. Stickers on the keys matched the aliens' colors, and response keys' color and left/right placement always matched the left/right alien color assignment on the screen.

Participants first pressed the spacebar to indicate that they were ready to begin a trial. Then a single, randomly selected 300-ms category exemplar played across five repetitions (50-ms interstimulus interval). Participants registered a categorization response. After a 500-ms delay, audiovisual feedback was delivered in the form of a smiley face and "Good job!" or a frowning face and "Oops!" A 1-s silent intertrial interval followed. The generalization posttest was identical to the training blocks except that there was no feedback. The experiment procedure was identical for children and adults.

Working memory

After the category training and generalization tasks, participants completed two measures of verbal working memory capacity: Forward Word Span and Backward Word Span (Godwin, Fisher, & Matlen, 2012). The word span task lists contained common count nouns from the MacArthur Communicative Development Inventory (Dale & Fenson, 1996). We used two nonoverlapping word lists and counterbalanced the order of word span tasks and the lists used for each task across participants. In the Forward Word Span task, participants were instructed to repeat the words the experimenter recited in the exact order that they were said. In the Backward Word Span task, participants were instructed to recite the words the experimenter said in the opposite order. The experimenter gave participants an example, and then a practice trial, before each task. The final word span length score was determined by the longest word list length that the participant was able to recite correctly. Inclusion of these measures supported examination of a possible relation between auditory II category learning performance and working memory capacity.

Results

Behavioral results

Category learning

As is evident in Fig. 2, adults were more accurate than children across all training blocks, $F(1, 62) = 67.60$, $p < 0.001$, $\eta_p^2 = 0.52$. Performance improved across blocks, $F(2.7, 164.9) = 19.00$, $p < 0.001$,

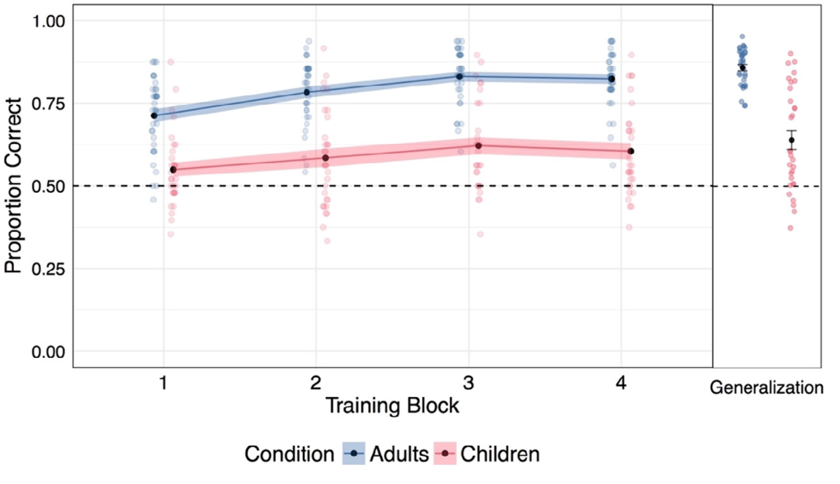

Fig. 2. Mean categorization accuracy across the four training blocks and in the generalization test for adults and children relative to chance (50%), represented by the dotted line. Individual data points indicate individual participants' proportions correct. Ribbon error bars represent standard errors of the means.

$\eta_p^2 = 0.23$ (Huynh–Feldt-corrected values), and the pattern of performance across blocks did not differ for adults and children, $F(2.7, 163.9) = 1.54$, $p = 0.21$, $\eta_p^2 = 0.024$ (Huynh–Feldt-corrected values). According to Bonferroni-corrected post hoc tests, each age group improved from Block 1 to Block 2 ($p = 0.006$) and from Block 2 to Block 3 ($p = 0.003$). Performance was not significantly different from Block 3 to Block 4 ($p = 1.00$) for either group.

Accuracy for adults was above chance (50%) even in the first block ($M = 71.3\%$ correct), $t(33) = 10.80$, $p < 0.001$, $d = 1.85$. Although children performed significantly worse than adults across training, children also had above-chance performance in the first block ($M = 54.9\%$ correct), $t(29) = 2.33$, $p = 0.026$, $d = 0.43$.

Adults also performed better than children in the generalization posttest, $t(35.6) = 7.21$, $p < 0.001$, $d = 1.85$ (Fig. 2, right panel). The average posttest accuracy for adults was 85.9% and was significantly above chance (50%), $t(33) = 37.00$, $p < 0.001$, $d = 6.34$. Children also demonstrated above chance performance in the posttest with an average accuracy of 64.0%, $t(29) = 4.87$, $p < 0.001$, $d = 0.89$. Learning fully generalized to novel exemplars, even when feedback was no longer present. Average performance in the generalization test was even more accurate than the average accuracy in Block 4 for both adults, $t(33) = 3.26$, $p = 0.003$, $d = 0.56$, and children, $t(29) = 2.16$, $p = 0.04$, $d = 0.39$.

Thus, adults outperformed 5- to 7-year-old children in auditory II category learning. Although children's performance was poorer than adults on average, there was considerable individual variability in accuracy across blocks and in the generalization posttest. As is evident in Fig. 2, some children performed at levels on par with adult participants. The variability in category learning outcomes, as evidenced in posttest generalization, was not related to children's age as calculated in decimal years based on each child's birthdate and the day of the experiment, $r(30) = 0.13$, $p = 0.50$.

To assess the potential involvement of the explicit system in driving responses during learning, we examined the relationship between working memory capacity and performance in the young children. This difference in performance among the children was not explained by differences in working memory capacity as assessed by the Forward Word Span and Backward Word Span assessments (Godwin et al., 2012) (Fig. 3). There was no correlation between children's posttest accuracy and either Forward Word Span length, $r(30) = 0.23$, $p = 0.22$, or Backward Word Span length, $r(30) = 0.11$, $p = 0.58$. In general, as may be expected, adults performed better than children on both Backward Word Span, $t(62)$

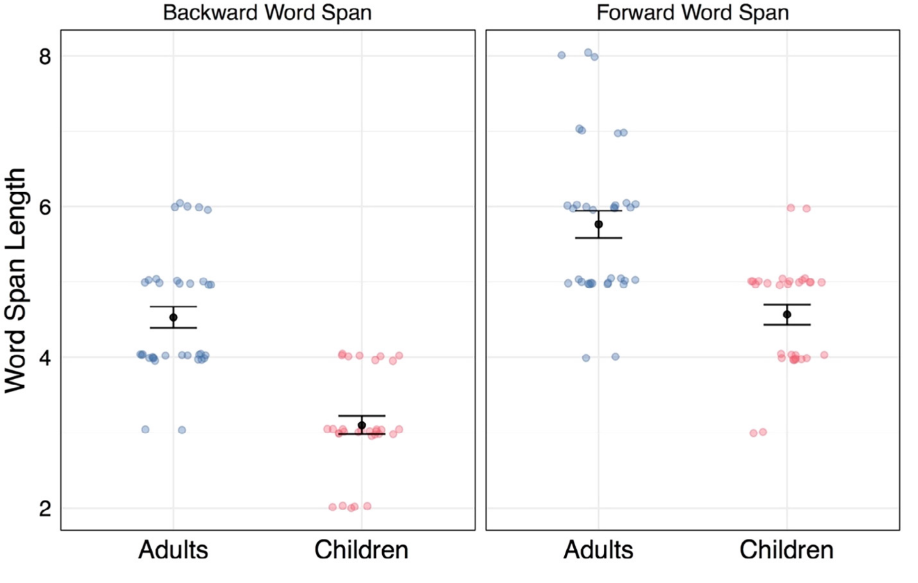

Fig. 3. Backward Word Span and Forward Word Span lengths for adults and children. Individual data points indicate individual participants' maximum word span lengths. Error bars represent standard errors of the means.

= 5.25, $p < 0.001$, $d = 1.91$, and Forward Word Span, $t(61.5) = 7.68$, $p < 0.001$, $d = 1.32$ (equal variances not assumed). The mean word span length for adults was 4.53 for Backward Word Span and 5.76 for Forward Word Span. The mean word span for children was 3.10 for Backward Word Span and 4.57 for Forward Word Span. Although there was considerably less variability in categorization performance for the adults, there was also no correlation between Backward Word Span and posttest accuracy, $r(34) = 0.14$, $p = 0.42$, or between Forward Word Span and posttest accuracy, $r(34) = 0.08$, $p = 0.67$, among adults. It is interesting to note that although the means are significantly different, there is some overlap in both the Forward Word Span and Backward Word Span for these college-aged adults and young children. We return to this point in the Discussion.

Computational modeling

To better understand how participants approached this category learning problem, and specifically how they used the dimensions to distinguish the categories, we applied decision-bound computational models to the category responses of each participant across learning and in the generalization posttest (Ashby & Maddox, 1993; Ashby, 1992). Decision-bound models are derived from general recognition theory (Ashby & Townsend, 1986) and assume that learners rely on category boundaries between distributions of category exemplars to make responses. These models have been applied extensively in the dual systems category learning literature with both auditory and visual categories (Ashby & Maddox, 2011; Maddox, Chandrasekaran, Smayda, & Yi, 2013; Scharinger, Henry, & Obleser, 2013). Examining the patterns in decision-bound strategy use across the experiment will enable examination of the interaction between the explicit and implicit systems across learning.

We applied four decision-bound models to the category learning response data: a unidimensional rule-based model based on the CF dimension, a unidimensional rule-based model based on the MF dimension, an II model, and a random responder model. The optimal model for the II categories learned in this experiment is the II model.

Unidimensional rule-based models

The two unidimensional rule-based models assume that learners use hypothesis testing strategies instantiated through the explicit system in the dual systems model (Ashby et al., 1998). The unidimensional models are best fit when participants rely on only a single dimension in category decisions. In other words, unidimensional strategies are best fit when participants selectively attend to only one of the dimensions. The two unidimensional models that we used were based on selective attention to either the CF or MF dimension. These models have two free parameters: the decision boundary and the variance of perceptual and criterial noise. An example of a unidimensional rule based on CF might be "If the tone is high on center frequency, it belongs to Category A; if it is low on center frequency, it belongs to Category B."

Information-integration model

The II model assumes that participants pre-decisionally integrate the two dimensions to create a linear decision bound that cuts diagonally through the stimulus distribution space. The II model instantiates the implicit procedural learning system in the dual systems model (Ashby et al., 1998). This II model is the optimal model for learning II categories such as those of this experiment.

Formally, the II model is a general linear classifier model that assumes a linear decision boundary to separate the two categories. This model has three free parameters: the slope of the decision boundary, the intercept, and the variance of perceptual and criterial noise. The integration models are much more difficult to verbalize, but the key factor is that the decision boundary uses both dimensions.

Random responder model

The random responder model assumes that participants guess on each trial.

Model fits

We fit the models separately to each participant's data from each of the four training blocks and the generalization posttest. The model parameters were estimated using a maximum likelihood procedure

(Ashby, 1992), and the models were compared using the goodness-of-fit Akaike's information criterion ($AIC = 2r - 2\ln L$, where r is the number of free parameters and L is the likelihood of the model given the data; Akaike, 1974). The AIC allows us to compare the fits of the models to the data and penalizes a model for extra free parameters. The model designated as the best-fit model for each participant for each block and the test was the model associated with the smallest AIC value.

Computational modeling results

The proportion of participants best fit by each model across blocks is shown in Fig. 4. This visualization enables examination of the switch from the explicit system to the implicit system, which is optimally suited for this II category learning problem. Ideally, participants would switch rapidly from using suboptimal rule-based strategies to using the optimal integration strategy. Examining how this pattern changes across learning for adults and children will illuminate how these systems are driving responses during learning in these age groups.

The pattern of best-fit models differs substantially across adults and children. Whereas nearly all adults were best fit by the optimal integration model throughout training, the majority of children were best fit by suboptimal unidimensional rule-based models. Adults were able to find and use the optimal integration strategy early in training, accounting for their excellent behavioral performance. Even in the first block, 67.6% of adult participants were best fit by the optimal integration model. This pattern continued across the rest of the training blocks. In the generalization test, 100% of adult participants were best fit by the optimal model.

In contrast, children overwhelmingly relied on a unidimensional strategy in the first block, with 53.3% of children best fit by a unidimensional-CF model, 33.3% best fit by a unidimensional-MF model, and only 13.3% best fit by the optimal integration model. Yet, some children used the optimal model throughout training and in the generalization test. In the generalization test, 43.3% of children were best fit by the optimal model.

Even though the children were using suboptimal strategies over the course of learning, they were not randomly guessing; no child or adult was best fit by a random responder model over the course of the entire experiment. To better understand how strategy use changed across learning, we examined the number of switches between different strategies for each participant. We classified a switch in strategy as a change from one class of best-fit models to another. For instance, if a participant was best

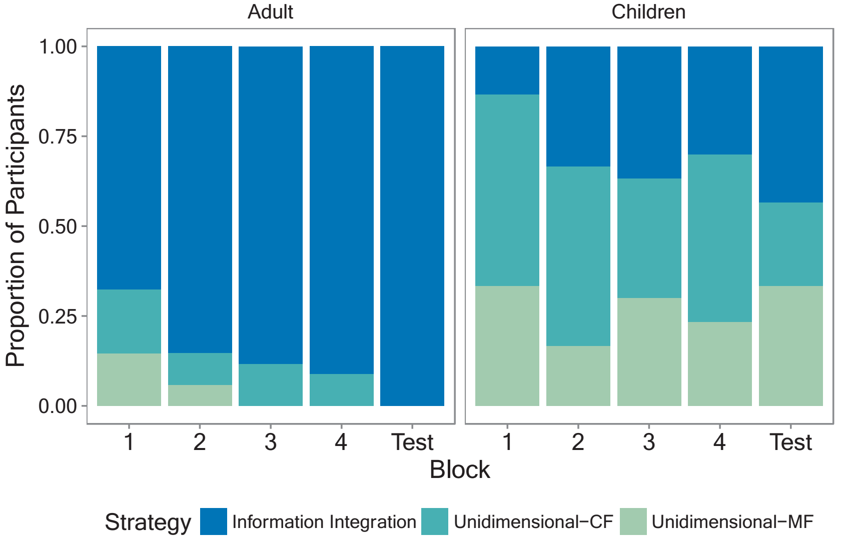

Fig. 4. Proportions of adults and children who were fit by each model (information integration, unidimensional-center frequency [CF], and unidimensional-modulation frequency [MF]) across all four training blocks and the generalization posttest.

fit by a unidimensional-CF model in Blocks 1 and 2 and then switched to a unidimensional-MF model for Blocks 3 and 4 and then back to a unidimensional-CF model for the test, we could count this as two switches.

Out of a maximum of four switches in best-fit strategy (between each block and the generalization test), adults switched strategies an average of 0.65 times (*Mdn* = 0). In contrast, children switched strategies an average of 2.20 times (*Mdn* = 2). Adults were able to find and use the optimal integration strategy very well even in the first block of training. In fact, more than half of the adult participants were best fit by the integration strategy in Block 1 and never switched strategies (19/34 participants). The children, on the other hand, switched strategies often. The vast majority of child participants switched strategies at least once (26/30 participants), and many switched more than once (5 made one switch, 8 made two switches, 7 made three switches, and 6 made four switches). To examine how the number of switches in strategy was related to category learning for the children, we computed the correlation between number of switches during the entire experiment and accuracy in the generalization test. For the children, there was a significant negative relationship between the number of switches in strategy and accuracy ($r = -0.47$, $n = 30$, $p = 0.0088$). Fewer switches in strategy was related to higher accuracy for the children. Interestingly, the 4 children who did not switch strategies at all during the entire experiment were all best fit by the optimal integration strategy, just as the majority of the adults.

By the end of training, some children were performing just as well as adults. To investigate whether this was due to adult-like strategy use by the end of category learning, we examined the relation between generalization posttest best-fit strategy and posttest accuracy. Indeed, as Fig. 5 shows, the children who were performing at similar levels as adults in the generalization posttest were also the children who were using the optimal strategy. The 13 children who were best fit by the optimal model had an average posttest accuracy of 80.15% compared with the adult average accuracy of 82.4%. Test accuracy for children best fit by the optimal model was significantly greater than chance, $t(12) = 16.72$, $p < 0.001$, $d = 4.64$, but was still lower than test accuracy for adults, $t(45) = 2.98$, $p = 0.005$, $d = 0.94$. In contrast, Children who were best fit by the unidimensional strategies in the posttest had accuracies near chance levels of performance. Children using the unidimensional-CF strategy had an average accuracy of 54.3% ($n = 7$), not significantly different from chance,

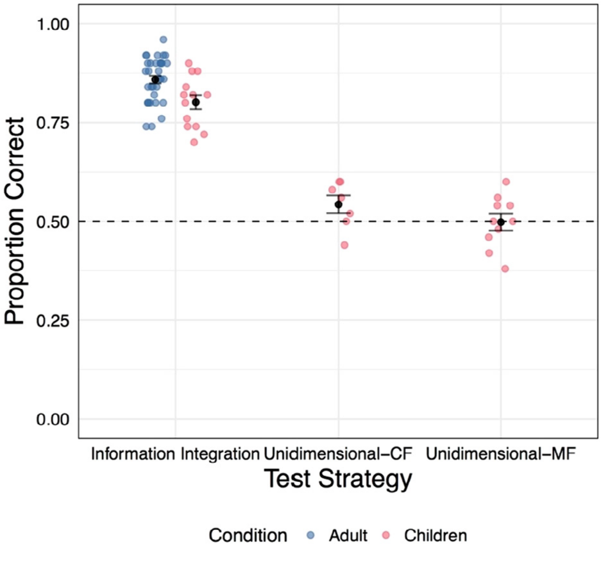

Fig. 5. Generalization posttest accuracy as a function of best-fit strategy for adults (all best-fit by information-integration model) and children. Error bars reflect standard errors of the means. CF, center frequency; MF, modulation frequency.

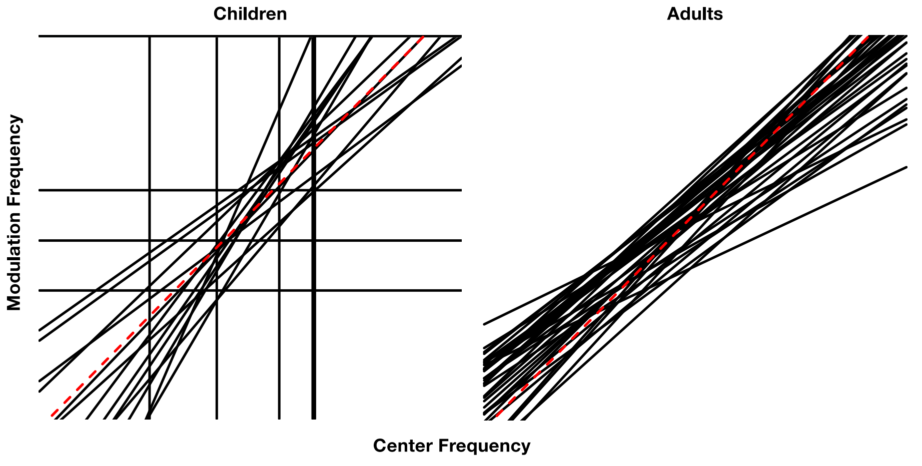

Fig. 6. Individual decision bounds for each participant separately in generalization test relative to optimal, which is represented by a dashed line.

$t(6) = 1.91$, $p = 0.11$, $d = 0.72$. Children using the unidimensional-MF strategy had an average accuracy of 49.8% ($n = 10$), not significantly different from chance, $t(9) = -0.095$, $p = 0.93$, $d = -0.03$. Considering children's learning separately from adults' learning, test strategy affected posttest accuracy, $F(2, 27) = 73.50$, $p < 0.005$, $\eta_p^2 = 0.85$. According to Bonferroni-corrected post hoc comparisons, the children using the integration strategy performed significantly better than the children using either of the unidimensional strategies (vs. unidimensional-CF: $p < 0.001$; vs. unidimensional-MF: $p < 0.001$). Those using the suboptimal rule-based strategies did not differ in posttest accuracy ($p = 0.50$). Furthermore, examining the mapping of individual decision boundaries in the generalization test for each participant relative to the optimal boundary, as in Fig. 6, makes it clear that the children best fit by the optimal integration strategy (diagonal lines) arrived at decision boundaries highly similar to those employed by adults.

Discussion

Adults outperformed 5- to 7-year-old children on an auditory category learning task requiring integration across multiple dimensions. There was substantial variability in learning for the children. Children who were able to adopt adult-like optimal integration decision strategies and switch control to the implicit system performed nearer to adult levels at posttest and learned significantly better than children who used suboptimal rule-based decision strategies. These differences in learning ability among the children were not correlated with age or verbal working memory capacity, as measured in the form of Forward Word Span and Backward Word Span tasks. Children also switched between the strategy types more often than adults, and children who switched fewer times had higher categorization accuracy. Below, we discuss the implications of these results for understanding the differences in II categorization ability in young children and adults. We also discuss these results as they relate to the potential interaction between the dual systems of category learning and the developmental trajectory of the perception of dimensions.

Development of information-integration category learning

A central goal of the study was to examine II category learning in young children (5- to 7-year-olds) to compare with both adults and studies of learning in older children. In line with the current results, a previous study of visual II category learning in older children (8- to 12-year-olds) demonstrated that older children learned II categories more poorly than adults (Huang-Pollock et al., 2011). In addition, similarly to the young children in the current study, the majority of the older children in that study relied on suboptimal unidimensional rules during learning. However, in the previous study, many adults also failed to use an optimal integration strategy. In the current study, adults were able to apply integration strategies early in training, and by the end of learning all adults were using the optimal strategy. Adults rapidly shifted control from the explicit system to the implicit system. Young children showed a slower shift and, like the older children in Huang-Pollock et al. (2011), used suboptimal rule-based strategies throughout learning. By the generalization test, 43% of the young children in our study were able to use the optimal integration strategy to categorize the sounds. Thus, the current study suggests that there are developmentally sensitive abilities in the shift of control from the suboptimal explicit system driving unidimensional strategies to the optimal implicit system during II category learning.

These results may suggest a role for developmentally sensitive regions, such as the PFC, in the switch of control from the explicit system to the implicit system. This is also consistent with a study on visual II category learning demonstrating that older adults struggled in switching from the explicit system to the implicit system, as seen through their overreliance on rule-based strategies (Rabi & Minda, 2017). Aging affects brain functioning in frontal regions in a way that mirrors the protracted development of the PFC in children (Greenwood, 2000, 2007). Together, these findings are consistent with a role of the PFC in switching control from the explicit system to the implicit system.

However, the current results seem to be inconsistent with several studies of visual II category learning in young children based on a family resemblance category structure. These studies report that even young children (3-, 5-, and 8-year-olds) learn as well as adults (Minda, Desroches, & Church, 2008; Rabi, Miles, & Minda, 2015). However, whereas the family resemblance categories of these previous studies used binary features to define visual categories, the current study used continuous dimensions to define auditory categories. It is possible that children may approach feature-based visual category learning differently than auditory category learning across continuous dimensions. Although the current study cannot speak to the similarity-based processing that is required for family resemblance structures, it will be informative for future research to examine how feature-based versus dimension-based II across visual versus auditory input influences category learning across development. The current study is the only study to examine II category learning in the auditory modality in young children and adults. To better understand the developmental trajectory of II category learning, it will be necessary to examine learning across a broader age range with categories defined by a single modality.

Interaction between explicit and implicit systems

The current study used a developmental approach to test competing hypotheses that arise from the mixed results in the existing literature regarding the impact of lower working memory capacity on II category learning. One hypothesis was that children might have shown *facilitation* in II category learning relative to adults if their lower working memory capacities *hasten* the shift from the default explicit system to the implicit system, optimal for the II category learning challenge. An alternative hypothesis was that children might have shown *impairment* in II category learning relative to adults if their lower working memory capacities *prevent* the shift from the explicit system to the implicit system. Overall, our results are in closer alignment with the *impairment/prevention* hypothesis.

The observed II category learning differences between adults and young children can be explained by poorer switching from explicit to implicit learning systems as a result of fewer working memory resources. Not only did adults have better accuracy than children, but also children generally showed an overreliance on suboptimal rule-based strategies and most failed to switch to the optimal integration strategy. However, the children who were able to switch to the integration strategy, and therefore to switch from the explicit system to the implicit system, performed near adult levels. Our results are consistent with the studies demonstrating that poorer II category learning is evoked by taxing working memory resources using a dual task paradigm (Miles et al., 2014; Zeithamova & Maddox, 2006) and is associated with lower working memory capacity in older children relative to adults (Huang-Pollock et al., 2011). Thus, our results support the hypothesis that reduced working memory capacity in young children compared with adults prevents or slows a shift from the explicit system driving motor output to the implicit system driving motor output rather than hastens this shift. We observed that adults very quickly adopted strategies consistent with the implicit system and that children spent longer time with suboptimal explicit system strategies.

Nevertheless, there were substantial individual differences in children's performance. Some children were able to learn the II categories well, whereas other children performed around chance. In the group of children, neither working memory capacity nor age was associated with the learning outcome differences. The young children had shorter word spans than adults, but these differences were relatively small. It is possible that adults and children might not differ enough on this task for it to reliably differentiate behavior within a single age group. In addition, because pure measures of pure working memory are difficult to design (see Lewandowsky, 2011), our measures of working memory capacity could have tapped into more general cognitive or executive functioning abilities or failed to capture the mechanism that underlies switching between explicit and implicit systems. In addition, it is possible that the working memory measure in the current research may have been colored by general language proficiency. Although all our adult participants were proficient in English and used English as their primary language in school, for some of them English was a second language. Because working memory can be used as a measure of second-language aptitude (Miyake & Friedman, 1998), it is possible that more a more homogeneous sample or a more language-neutral working memory task might reveal greater variability between adult and child participants. Future research examining developmental populations with a broader survey of tasks would help to determine the cognitive processes that might be involved in switching between the dual systems and whether such switching is the driver of developmental differences in II category learning.

Finally, as we noted in the Introduction, poorer II category learning in children relative to adults might be evidence for a role that is also consistent with a single system perspective on category learning (Newell et al., 2011). Some studies demonstrating improved II category learning with impairments or taxes on working memory resources have been critiqued in favor of a single system perspective (for DeCaro, Thomas, & Beilock, 2008, see Tharp & Pickering, 2009; for Filoteo et al., 2010, see Newell et al., 2013; for Zeithamova & Maddox, 2006, see Newell et al., 2010, 2011). The current study was not designed to distinguish between dual systems and single system accounts, nor is this distinction critical for our primary conclusions. With that being said, future research should attempt to disambiguate dual systems and single system accounts within the realm of auditory category learning. Our current findings are consistent with both a single system account and a dual systems account whereby the interaction between the implicit and explicit systems is mediated in some way by the PFC.

Developmental trajectory of perception of dimensions

The application of the COVIS model to the auditory modality has generally demonstrated clear parallels between auditory and visual category learning mechanisms (Chandrasekaran, Koslov, et al., 2014; Chandrasekaran, Yi, et al., 2014; Maddox & Chandrasekaran, 2014; Reetzke et al., 2016; Yi & Chandrasekaran, 2016; Yi et al., 2016). However, a recent study points to potential differences between the visual and auditory modalities that may contribute to learning proceeding differently depending on the nature of the dimensions that define the categories (Roark & Holt, 2019).

Acoustic dimensions in general may be more difficult to selectively attend to than many visual dimensions for both children and adults. Dimensions contributing to complex auditory categories, such as speech, are difficult to selectively attend to, and in general auditory dimensions are likely more integral than visual dimensions (Garner, 1974). This general characteristic is likely true of the dimensions in the current study as well. Previous studies have shown that adults have difficulty in selectively attending to the dimensions used to construct the categories in the current study even when it is required by the learning task (Holt & Lotto, 2006). Similarly, in the current study, we found patterns that are typically not observed with either visual or auditory category learning in that adults were using integration strategies early on rather than beginning with simple unidimensional strategies (Ashby & Maddox, 2011; Ashby et al., 1999). A majority of the adults in the current study used optimal integration strategies even in the first block. It could be the case that adults very rapidly switch from the explicit system to the optimal implicit system. However, it is also possible that for these particular acoustic dimensions the implicit system is the default system for adults.

In addition, the pattern of perception of dimensions as integral or separable changes across development. Whereas young children tend to perceive stimulus dimensions as integral, adults can better selectively attend to perceptually separable dimensions (Kemler & Smith, 1978). During categorization, children tend to rely on multiple input dimensions, whereas adults selectively attend to individual dimensions (Deng & Sloutsky, 2015; Plebanek & Sloutsky, 2017; Sloutsky, 2010). Moreover, children are more likely to respond to category exemplars based on exemplar similarity—a holistic strategy—than on rule-based strategies (Kemler Nelson, 1984; Kloos & Sloutsky, 2008; Minda & Miles, 2009). The shift from perceiving stimulus dimensions as integral to separable is thought to occur between 5 and 8 years of age (Kemler & Smith, 1978; Smith & Kemler, 1978). Interestingly, the young children in the current study more often used suboptimal rule-based strategies that rely on selective attention, whereas the adults used an integration strategy, which is the opposite of this typical developmental pattern. In general, it will be important for future research to examine how the nature of the input dimensions across which categories are defined influences the developmental differences in category learning.

In sum, the current study is consistent with a perspective suggesting that II category learning involves developmentally sensitive brain regions insofar as the shift from the default explicit system to the implicit system is required. We observed that adults rapidly adopted optimal integration strategies that may reflect an early switch to the implicit system, which is accompanied by relatively high accuracy. In contrast, young children more frequently used suboptimal rule-based strategies and struggled to switch control to the optimal implicit system. However, those children who did switch control to the implicit system and were best fit by the integration strategy model performed near adult levels.

We investigated learning of novel auditory categories in young children and adults to better understand the mechanisms available to support the learning of speech categories during childhood. We observed that the strategy use of children was starkly different from adults. Part of learning to be an expert during category learning includes learning to tune into the relevant information and use it in an optimal way. Although it is often assumed that this ability is complete during infancy, phonetic category learning is not adult-like until after 12 years of age (Idemaru & Holt, 2013; Nittrouer et al., 1993; Nittrouer, 2004; Zevin, 2012). Our results underscore that auditory abilities, including auditory category learning, continue to develop throughout childhood and there can be large differences in performance and strategy use during learning. It is important to acknowledge that auditory category learning—a process that contributes to speech perception—does not end during infancy so that future research can be directed toward the discovery of the developmental course of auditory category learning.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jecp.2019.104673.

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