The role of lexical status and individual differences for perceptual learning in younger and older adults

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Abstract

Purpose: This study examined whether older adults remain perceptually flexible when presented with ambiguities in speech in the absence of lexically disambiguating information. We expected older adults to show less perceptual learning when top-down information was not available. We also investigated whether individual differences in executive function predicted perceptual learning in older and younger adults.

Method: Younger (n=31) and older adults (n=27) completed two perceptual learning tasks comprised of a pretest, exposure, and posttest phase. Both learning tasks exposed participants to clear and ambiguous speech tokens, but crucially, the lexically-guided learning task provided disambiguating lexical information, while the distributional learning task did not. Participants also performed several cognitive tasks to investigate individual differences in working memory, vocabulary, and attention-switching control.

Results: We found that perceptual learning is maintained in older adults, but that learning may be stronger in contexts where top-down information is available. Receptive vocabulary scores predicted learning across both age groups and in both learning tasks.

Conclusions: Implicit learning is maintained with age across different learning conditions, but remains stronger when lexically biasing information is available. We find that receptive vocabulary is relevant for learning in both types of learning tasks, suggesting the importance of vocabulary knowledge for adapting to ambiguities in speech.

Introduction

Listeners regularly encounter unexpected variation in speech, to which they must adapt in order to successfully perceive the signal. Various causes for these idiosyncrasies include accent and dialect differences, speech production disorders or impediments, and noisy environments. It is well established that young, normal-hearing listeners are able to quickly adapt to a great deal of variability to successfully recognize speech. Normal aging effects, like high-frequency hearing loss and declines in temporal processing, impact the successful speech perception of older adults (Pichora-Fuller & Souza, 2003). This is reflected in experimental evidence showing more gradual, less defined phonetic categorization (Bidelman, Villafuerte, Moreno, & Alain, 2014) and poorer word recognition in noise (Helfer & Freyman, 2014). Despite these challenges, older adults remain capable of performing comparably to a younger cohort in certain speech tasks, especially if supportive context is available, like that provided by redundant cues in the input or information stored in memory (Pichora-Fuller, 2008). We are interested in perceptual flexibility in younger and older adults, as well as the role various cognitive functions play in maintaining perceptual flexibility in older adults, especially the role of top-down lexical knowledge, given older adults' use of top-down strategies in other speech tasks (see Pichora-Fuller, 2008, for review).

Perceptual learning, as pertains to speech, covers a wide range of learning phenomena (see Samuel & Kraljic, 2009, for review), and here we will focus on the aspects of perceptual learning that affect phonetic retuning (sometimes also referred to as phonetic recalibration; Bertelson, Vroomen, & De Gelder, 2003, for example). That is, we are concerned with the adaptation of phonetic categories in response to variation in the speech signal. We use the terms perceptual learning and perceptual flexibility to refer to the short-term adaptation of speech representations in response to brief exposure to manipulated speech input. To further investigate how perceptual learning may be affected by aging, we specifically focus on two types of learning – lexically-guided learning and distributional learning – to contrast the influence of lexical knowledge and other cognitive and sensory factors in different types of perceptual learning.

Norris, McQueen, and Cutler (2003) first established the lexically-guided learning paradigm by presenting listeners with manipulated speech which contained an ambiguous word-final phoneme. For one group of listeners, this ambiguous sound (henceforth, [?]), which fell acoustically between /f/ and /s/, replaced all instances of /f/ in the stimuli, while for another group, [?] replaced /s/. For example, listeners exposed to ambiguous /s/ would hear "octopu?" rather than "octopus", while listeners exposed to ambiguous /f/ would hear "gira?" rather than "giraffe". After brief exposure to these ambiguous phonemes within real words, it was found that the two exposure groups had shifted their category boundaries between /f/-/s/ in opposite directions to accommodate for the ambiguity (i.e., the group that heard [?] in place of /f/ categorized more tokens as /f/ and the group that heard [?] in place of /s/ categorized more tokens as /s/). Thus, it was argued that lexical information played an important role in this kind of learning, given that listeners would be biased to perceiving the tokens with [?] as real words rather than nonwords. Furthermore, no such difference was found between exposure groups when participants were exposed to the ambiguous fricative at the end of a nonword accompanied by clear tokens of either /s/ or /f/ in real words, strengthening the claim that the effect was due to a lexical bias when hearing the ambiguous sound.

The category shift that results from lexically-guided learning relies on the embedding of the ambiguous sound within a real word. The second paradigm we investigate, distributional learning, does not depend on lexical information, but can yield shifts in category boundaries on the basis of the relative frequency of clear and ambiguous tokens. With distributional learning, exposure to a manipulated distribution of speech sounds leads to a shift of the phonetic category boundary, which reflects the shape of the distribution. For example, Kleinschmidt and Jaeger (2015a) provided evidence that listeners shift their category boundaries based on exposure distributions of manipulated voice onset time (VOT), but also showed that the magnitude of the shift is constrained by listeners' prior beliefs about a category (i.e., listeners update their existing category boundary to incorporate new information from the distribution). Unlike Clayards et al. (2008), which used distributions of different variances to manipulate the slope of listeners' boundaries, Kleinschmidt and Jaeger (2015a) used distributions with different means to manipulate listeners' boundary locations. These initial investigations used real word stimuli, begging the question as to the role of lexical knowledge in the boundary shift. Schreiber, Onishi, and Clayards (2013) exposed listeners to a *nonword* continuum designed to shift the location of the category boundary between /n/ and /m/; results provided evidence that distributional learning still takes place in the absence of lexical or contextual information.

Perceptual learning has generally been described as a form of implicit learning, which is supported by explanations for both lexically-guided and distributional learning. Kleinschmidt and Jaeger (2015b) propose an "ideal adapter" framework to account for the challenges faced in speech perception, including adapting to novel talkers. Under this framework, listeners adapt to novel situations by comparing how well each representation predicts the input. In other words, listeners must use their prior beliefs about a category and track the distribution of relevant cues from the talker to update their phonetic category successfully. Lexically-guided learning has been accounted for in a similar way, whereby higher-level representations are compared to the speech input and internally-generated error signals drive adaptation (Guediche, Fiez, & Holt, 2016). Learning in these tasks does not depend on explicit attention to the nature of the stimuli, providing further support for its implicit nature. For example, Schreiber et al. (2013) used passive exposure while participants performed an unrelated visual search task. Passive exposure to the stimuli has also been shown to be effective for lexically-guided learning (Eisner & McQueen, 2006; McQueen, Norris, & Cutler, 2006).

The above-mentioned studies all investigate perceptual flexibility in young, normal-hearing adults, but we are especially interested in what happens to flexibility in normal aging. Older adults have more difficulty recognizing speech, especially in noise (Helfer, Merchant, & Freyman, 2016), and have a harder time recognizing degraded phonemes (Schvartz, Chatterjee, & Gordon-Salant, 2008) compared to younger adults. However, older adults can also perform comparably to younger adults in certain tasks (for example, the benefit of repetition for recognizing speech is similar across younger and older adults; Helfer & Freyman, 2016), and it has been suggested that older adults develop compensatory strategies for age-related sensory declines in order to successfully recognize speech (Pichora-Fuller, 2008).

To date, the studies investigating perceptual learning in older adults have all utilized paradigms that rely on top-down lexical information (e.g., Adank & Janse, 2010; Golomb, Peelle, & Wingfield, 2007). Scharenborg and Janse (2013) compared lexically-guided learning in a group of older and younger adults, and found overall that the age groups performed comparably, but there were differences in their behaviour across blocks. Specifically, older adults' learning remained more stable, while younger adults showed more unlearning after greater initial learning. Neger, Rietveld, and Janse (2014) also found no difference in the perceptual learning abilities of younger and older adults in a sentence repetition task which used noise-vocoded stimuli as the speech that needed to be learned. In this instance, the learning trajectories across blocks were the same for the two age groups in the perceptual learning task, but differed in a visual statistical learning task. These results suggest that perceptual learning is sustained in aging. However, evidence of comparable flexibility in younger and older adults does not guarantee that the mechanisms underlying perceptual learning remain the same over the course of the lifespan.

Top-down strategies play an important role in the speech perception of older adults, and the influence of lexical knowledge on speech categories is especially of interest here. Pichora-Fuller (2008) reviews compensatory strategies employed by older adults, and outlines how lexical knowledge (including word frequency and word familiarity) influences word identification during speech in noise tasks (with more frequent or more familiar words being correctly identified more often). Ganong (1980) established that listeners are biased towards perceiving ambiguous stimuli as real words rather than nonwords, even when instructed to identify only a single target sound within the stimuli. For example, an ambiguous token that falls between ‘stop’ and ‘stob’ is more likely to be perceived as the real word ‘stop’ and have the final consonant identified as /p/ than be perceived as the nonword ‘stob’ with a final consonant of /b/. Baum (2003) and Mattys and Scharenborg (2014) found that older adults show an increased lexical bias compared to younger adults, such that they are even more biased to perceiving unclear tokens as words rather than nonwords. Older adults also have more difficulty inhibiting high-frequency lexical competitors (Revill & Spieler, 2012) and recognizing words that have many neighbours (Sommers & Danielson, 1999) compared to younger adults, suggesting that older adults are susceptible to a variety of lexical effects that may result from an overall increase in reliance on top-down information.

Since the influence of lexical items has been shown to be crucial to learning, and older adults have shown bigger lexical effects, we might expect older adults to show more learning than younger adults. Thus, the comparable learning observed could indicate that the increased reliance on top-down information is compensating for weaker implicit learning. On the other hand, there is some evidence that implicit learning remains mostly unaffected by age. Midford and Kirsner (2005) used an artificial grammar-learning task and found that older adults performed comparably to younger adults under manipulations that targeted implicit learning, but performed worse when explicit learning was targeted. We aim to test whether perceptual learning for speech in older adults relies on support from top-down information by contrasting performance in lexically-guided and distributional learning tasks, the latter of which includes no influence of lexical status.

Given that speech perception in less-than-ideal conditions can be cognitively demanding, the influence of various cognitive abilities on perceptual learning in older adults is also of interest. Previous studies investigating perceptual learning in older adults have found evidence for individual differences in the influence of cognitive abilities on learning (Scharenborg, Weber, & Janse, 2015). We focus here on several aspects of executive and cognitive functioning that may play a role in maintaining perceptual flexibility, including attention-switching control, working memory, vocabulary size, and hearing-in-noise ability.

Directing attention to the idiosyncratic nature of the stimuli during a lexically-guided learning task has been found to be detrimental to perceptual learning, compared to when attention remains focused on the task (McAuliffe & Babel, 2016). Scharenborg et al. (2015) found that older adults with poorer attention-switching control show more learning-consistent behaviour than those with better attention-switching control. Taken together, these findings suggest that individuals with better attention-switching control alternate their attention between the acoustic signal and the lexical decision task, while those with poorer attention-switching control remained focused on the task, which is beneficial for lexically-guided learning. We expect to replicate the findings of Scharenborg et al. (2015), such that older adults with poorer attention-switching control will show more learning in the lexically-guided learning task.

Given the lexical motivations for this study, vocabulary size is also of interest in regards to its role in perceptual learning in older adults. Baese-Berk, Bent, Borrie, and McKee (2015) previously found that receptive vocabulary scores are related to the perception of unfamiliar speech in younger adults. Mattys, Davis, Bradlow, and Scott (2012) also linked larger receptive vocabulary to better speech-in-noise recognition in younger adults. If the same relationship found by Baese-Berk and colleagues (2015) holds for older adults, those with larger receptive vocabularies will show more learning, especially in the lexically-guided learning task where a top-down influence is expected.

There is conflicting evidence as to what the influence of working memory and hearing sensitivity may be on perceptual learning. It is possible that working memory facilitates perceptual learning by maintaining auditory stimuli in an accessible way, with individuals who have better working memory being more able to maintain and manipulate stimuli mentally. While hearing sensitivity has not been found to play a specific role in lexically-guided learning (Scharenborg et al., 2015), distributional learning may rely more on perceptual acuity and thus hearing sensitivity may be related to the amount of learning seen in such a task. We also include a measure of hearing-in-noise ability, the Speech in Noise Test (SPIN, Bilger, Nuetzel, Rabinowitz, & Rzeczkowski, 1984). This test provides a measure of how well older adults perform with speech in noisy conditions, and also includes high and low predictability sentences, which provide a measure of how much individuals benefit from supportive context.

Given that previous evidence for perceptual learning in older adults has only been investigated using paradigms that rely on lexical status (e.g., lexically-guided learning or adapting to noise-vocoded speech) and that harnessing top-down information is one strategy for older adults to compensate for perceptual declines in their auditory systems, the present study asks whether older adults still remain perceptually flexible in the absence of lexically-disambiguating contexts. Using both lexically-guided and distributional learning tasks, and a series of cognitive measures, we investigate whether younger and older adults perform differently when lexical status plays a role in exposure and whether individual differences in cognitive measures predict learning in either perceptual learning task. We expect older adults to show comparable learning to younger adults in the lexically-guided learning task (as in Scharenborg & Janse, 2013), but that age may affect learning in the distributional learning task, where no additional lexical information is available, resulting in less learning for the older adults in this task. We further test whether individual differences in several sensory and cognitive factors predict perceptual flexibility in each of these learning tasks, under the assumption that variation in these factors likely influences the amount of perceptual learning in an individual.

Because we are interested in comparing two perceptual learning tasks, it is necessary to guard against any possible confounds that may arise when testing the same participants on multiple learning paradigms. Kraljic and Samuel (2007) found that certain phonetic manipulations (i.e., temporal ones) would generalize across talkers, while others (spectral manipulations) would not. We thus chose to manipulate vowels for our learning tasks and to use different voices for the presentation of the two tasks. We also assigned the participants to different conditions across tasks, such that their boundaries should be shifted in different directions. Finally, we use a pretest-posttest (Eisner & McQueen, 2006) design for both tasks to control for the baseline performance on both tasks.

Method

Participants

A group of 31 younger adults (ages 18-29, M=20.7) recruited from the McGill University community, and a group of 31 older adults (ages 63-87, M=69.7) recruited from the greater Montreal community participated in this study. All participants were native speakers of English, and some had exposure to a second language. 27 older adults and 17 younger adults had some knowledge of a second language, but none were exposed to their second language before the age of 5 (M_{age}=10.5), and no one rated their second language proficiency any higher than an intermediate level. Participants whose Pure Tone Average (PTA) in their better ear was greater than 25 dB were excluded from any analysis. This resulted in four older adults being excluded from further analysis, leaving 27 older adult participants (M_{PTA-OA}=12.03). No younger adults were excluded on the basis of PTA (M_{PTA-YA}=1.29). All participants completed the same background measures, outlined below.

Background Measures

1. Hearing Screening
2. Trail-Making Test for attention-switching control
3. Backward Digit Span for working memory
4. Speech perception in noise (SPIN) Test
5. Peabody Picture Vocabulary Test-III (PPVT) for vocabulary knowledge

Hearing screening. Participants' hearing thresholds at the octave frequencies from 250 to 8000 Hz were measured using a GSI 61 Clinical Audiometer. Tones were presented over headphones in a sound-attenuated booth. Pure-tone average threshold was calculated as the average over 500, 1000, and 2000 Hz for each participant.

Trail-making Test. To measure attention-switching control, participants completed a computerized version of the Trail-making Test (TMT; Reitan, 1958) using PEBL (Mueller & Piper, 2014). Scharenborg, Weber, and Janse (2015) used a paper-and-pencil version of TMT to investigate attention switching, but the computerized version has been validated against the classic version (Piper et al., 2012), so our results should be comparable. TMT has two conditions: (a) for part A, participants must connect a series of numbered circles that are randomly scattered on the screen in ascending order (from 1-25); (b) for part B, participants must connect 25 circles alternating between numbers and letters (1-A-2-B-3-C, etc.). Attention switching control was measured as the ratio of response times between part A and B (TMT-B/TMT-A). The TMT took around 2 minutes to complete.

Backward Digit Span. A computerized version of the backward digit span task was used as a measure of working memory. The task was presented using PEBL (Mueller, 2011; Mueller & Piper, 2014). Digits are presented simultaneously on screen and over headphones one at a time, and participants report the list they hear in reverse order. Lists started at two digits in length and end at eight, with two different lists per length for 16 trials total. Each digit was visually presented for 1000 ms. Digit span was calculated as the proportion of correctly reported sequences (Neger et al., 2014). The digit span task took approximately 5 minutes.

Speech Perception in Noise. Participants were asked to repeat the last word of the sentence presented in speech-shaped babble noise. Half of the final words are highly predictable from the sentence context and half are low predictability for a total of 50 trials (Bilger, Nuetzel, Rabinowitz, & Rzeczkowski, 1984). The sentence stimuli were presented 50 dB louder than the participant's estimated threshold, and babble noise was presented 8 dB lower than the sentences (SNR = 8 dB). SPIN was scored as the difference between the total number of correctly identified sentence-final words in high predictability sentences and low predictability sentences. The SPIN task took approximately 10 minutes to complete.

Peabody Picture Vocabulary Test-III. The PPVT-III (Dunn & Dunn, 1997) is a multiple choice receptive vocabulary test where participants match pictures to a verbally presented vocabulary item. The raw scores were used as an indicator of vocabulary size. The test took 10 minutes to administer.

Perceptual learning tasks

Two perceptual learning tasks were designed to shift the category boundary between /ɛ/ - /ɪ/. Both used a pretest-exposure-posttest design, which will be further outlined below, with the exposure phase being the crucial difference between the lexically-guided and distributional learning tasks. Lexically-guided learning studies generally do not use pretest-posttest designs over concern that pretest exposure will block any learning from occurring (although such designs have been used with success, see Eisner & McQueen, 2006, for example). However, using a pretest-posttest design for both tasks allows us to employ a consistent analysis across both tasks, and is also more sensitive to actual learning effects while downplaying individual variability in categorization behaviour. Thus, we can be more confident that our results reflect an actual change in behaviour, rather than incidental pre-existing differences between groups.

Pretest-Posttest. For both learning tasks, five steps of an /ɛd-ɪd/ continuum were randomly presented 6 times each for a total of 30 trials per block. One block was presented during the pretest and three blocks were presented during the posttest (90 trials). The posttest was presented as three consecutive blocks immediately following the exposure phase because previous perceptual learning work comparing older and younger adults found different patterns of learning between the two age groups as the posttest progressed (Scharenborg & Janse, 2013). The pretest lasted about 2 minutes, and the posttest took approximately 6 minutes.

Lexically-guided learning. Two exposure lists were created for use in a lexical decision task: one with the ambiguous /ɛ/ tokens and the clear /ɪ/ (/ɛ/-amb), and the other with the ambiguous /ɪ/ tokens and the clear /ɛ/ (/ɪ/-amb). In addition to the 20 ambiguous target items and 20 control items, 60 filler words and 100 nonwords were presented for a total of 200 exposure trials. Word length (number of syllables) was the same for the two exposure lists (range=1-3 syllables, mean= 1.45), and there was no difference in word frequency between the lists ($t(34)=-0.29$, $p>0.05$), based on information drawn from the MRC Psycholinguistics Database (Wilson, 1988). The full list of items is in Appendix A. The exposure phase for the lexically-guided learning task lasted approximately 15 minutes.

Distributional learning. Two distributions were designed for use in a two-alternative forced choice task (2AFC), such that participants' category boundaries would shift towards one end of the continuum or the other, depending on the exposure condition. As shown in Figure 1, the /ɛ/-amb condition shifts the category boundary towards the /ɪ/ end of the continuum (more /ɛ/ responses), while the /ɪ/-amb condition shifts the category boundary towards the /ɛ/ end (more /ɪ/ responses). Twelve CVC minimal pairs were chosen to form the distributions, and were controlled for word frequency ($t(16)=-1.11$, $p>0.05$). The layout of the distribution was designed to be similar to the lexically-guided exposure, in that one end of the category has been entirely shifted into the more ambiguous portion of the continua, with no clear exemplars. For example, the /ɛ/-ambiguous condition presented clearer tokens from the /ɪ/ end of the continua, and ambiguous tokens for the /ɛ/ category (vice versa for the /ɪ/-ambiguous condition). These distributions represented one block of the exposure phase (132 trials), which was presented four times for a total of 528 trials. The exposure phase for the distributional learning task lasted approximately 40 minutes.

[INSERT FIGURE 1 NEAR HERE]

Stimuli

Two younger adult speakers of Canadian English (one male, one female) recorded all the stimuli. Two voices were chosen to try to avoid any influence that one learning task may have on the other, given that previous research has shown that lexically-guided learning is sometimes talker-specific, especially when the manipulation affects spectral information (Kraljic & Samuel, 2007), as is the case here. The speakers recorded all of the stimuli in isolation in a sound-attenuated room.

Pretest-Posttest. An 11-step syllable continuum (/ɛd-ɪd/) was created to use for pre- and post-testing. The syllables were created by splicing off the initial consonant from a monosyllabic word ("bed" or "bid") in Praat (Boersma & Weenik, 2014) and using Tandem STRAIGHT (Kawahara et al., 2008) to create the continuum from the two endpoints. Six participants (M_{age}=21.0) piloted the test continuum in a 2AFC task to ensure the category boundary fell in the middle of the continuum. After piloting and based on previous work (Scharenborg & Janse, 2013; Scharenborg et al., 2015), steps 4, 6, 7, 8, and 10 were chosen from the original 11-step continuum for use in the pre- and post-tests.

Lexically-guided learning. For the exposure phase, 20 English words with /ɛ/ in the final syllable (e.g., *upset*) and 20 words with /ɪ/ in the final syllable (e.g., *violin*) were chosen as the target words, such that replacing the target vowel in these words with the alternative (i.e., /ɛ/ or /ɪ/) resulted in a nonword. There were no other instances of these vowels anywhere else in the stimuli. All words had stress on the final syllable. The 40 nonword equivalents (e.g., *upsit* and *violen*) were also recorded. Additionally, 60 words with no /ɛ/ or /ɪ/ were selected as fillers, and 100 nonwords with no instance of /ɛ/ or /ɪ/ were created. The nonwords were formed by changing one or two sounds per syllable from English words (e.g., *koom* from *boot*). To make the ambiguous tokens, 40 word-nonword (e.g., *upset-upsit*) continua of 11 steps were created in Tandem STRAIGHT (Kawahara et al., 2008).

The 40 continua were then presented to 28 pilot participants (M_{age}=23.8; 14 participants heard the female voice, 14 participants heard the male voice), who were asked to categorize the target vowel in the stimuli in a 2AFC task. Based on these pilot data, the ambiguous token from each word-nonword continuum was selected as the point at which participants categorized the real word vowel 70% of the time (e.g., for the *upset-upsit* continuum, the step at which participants responded /ɛ/ 70% of the time). This criterion was used rather than the 50% point because of the inherent lexical effect that would have skewed responses towards the word end of the continuum (Reinisch & Holt, 2014).

Distributional learning. 12 minimal pairs were initially chosen to create the distributions for the exposure phase of the distributional learning task. Each minimal pair was turned into a 31-step continuum using Tandem STRAIGHT. The same 28 participants piloted the minimal pair continua, and one minimal pair was thrown out due to poor categorization (responses were overwhelmingly biased towards one end of the continuum), leaving 11 continua from which to make distributions (see Appendix A). Based on the pilot data, 11 steps from each original 31-step continuum were chosen for use in the exposure phase, using a similar method to

Schreiber et al. (2013) (i.e., if piloting revealed a bias towards one end of the continuum or the other, the chosen steps would be shifted to account for this).

Procedure

Testing was completed across two sessions of approximately one hour each. The hearing screening was completed during an earlier session as part of a separate study. During the two sessions, participants completed the learning tasks and all the cognitive tasks (TMT, Digit Span, PPVT, and SPIN). Given the length of the distributional learning task, it was completed by itself in one session (Session A), and the lexically-guided learning task and background measures were completed in another session on a separate day (Session B; see Table 1 for a breakdown of tasks). The order of the learning tasks was counterbalanced so that half of the participants completed the lexically-guided learning task in the first session, while the other half completed the distributional learning task during the first session. The order of voices (male first vs. female first), assignment of voices to tasks (e.g., male voice to lexically-guided task, female to distributional) and assignment of ambiguity conditions to voices and tasks (e.g., /ɛ/-amb to male lexically-guided task, /ɪ/-amb to female distributional) was also counterbalanced (see Table 2 for full counterbalancing).

[INSERT TABLES 1 & 2 NEAR HERE]

Results

Statistical Analyses

To investigate the learning effects in the two types of perceptual learning tasks, we analyzed participants' categorization responses in the pre- and posttests for both tasks. Figure 2A presents proportion /ɛ/ responses from the pre- and posttest for both the distributional and lexically-guided learning data by age group and exposure type, which illustrates the shift in the category boundary after exposure in both tasks (note that the three blocks of the posttest have been collapsed for this illustration). Responses were recoded according to whether or not they were consistent with the expected shift (so-called learning consistency, as in Scharenborg et al., 2015). For example, an /ɛ/ response from someone in the /ɛ/-ambiguous group is coded as ‘consistent’ (1), while an /ɪ/ response would be ‘inconsistent’ (0). This coding scheme allows us to analyze both exposure groups at the same time, in terms of a shift in their categorization behaviour in the predicted direction (i.e., an increase in learning consistency from the pretest to the posttest), rather than whether the exposure groups differ from each other at the posttest. Figure 2B displays the pre- and posttest categorization data in terms of learning consistency rather than proportion /ɛ/ responses (note that Continuum step has been recoded for Figure 2B, as discussed below). Learning consistency was then used as the dependent variable in mixed effects logistic regression models to compare learning in the two age groups, with one model for each learning task (Distributional and Lexically-guided). Blocks were Helmert coded so that comparisons could be made across different levels (Pretest vs. entire Posttest, Posttest block 1 vs. Posttest block 2-3, and Posttest block 2 vs. Posttest block 3), to investigate whether learning persisted across posttest blocks. Because the dependent variable has been coded such that it relies on a participant’s assigned exposure group, we also recoded Continuum Step so that an increase in step represents an increase in learning consistency, rather than an increase corresponding to a decrease in /ɛ/ responses. Thus, Continuum Step varies from the learning inconsistent category to the consistent one, rather than from /ɛ/ to /ɪ/. This allows for continuum step to remain interpretable when we include both /ɛ/- and /ɪ/-amb exposure groups in one model; otherwise continuum step would be conflicting for the two exposure groups – with an increase in step representing an increase in learning in one group and a decrease in the other. To highlight our question of interest, Figure 2C averages the learning consistent behaviour of the two age groups across continuum steps to make the change in learning consistency from pre- to posttest more evident.

[INSERT FIGURE 2 NEAR HERE]

The models reported below include the main effect of Continuum step and the two- and three-way interactions between Age group, Exposure group, and Block (along with their main effects). These models are of interest because the interaction between age group and block addresses our aging hypothesis while retaining several significant two- and three-way interactions that explain additional variation in the data. We also ran two full interaction models that included Voice (male/female) and Order (whether the distributional learning task was completed first or second) to ensure that there were no unwanted effects of the stimuli or order on learning. These models are reported in Appendix B and will be briefly discussed below. Age group, Voice, Continuum Step, and Order were rescaled and centered around zero. Random slopes by participant were included for all within-subject effects (Continuum Step and Block).

Lexical Decision

Participants accepted the ambiguous targets from the exposure phase of the lexically-guided learning task as real words 88.3% of the time. There were no participants who accepted less than half (10/20) of the ambiguous targets as real words. Table 3 shows the breakdown of percentage ‘yes’ response by age group and exposure type (/ɛ/ was ambiguous vs. /ɪ/) for the control and ambiguous targets. Given that we chose a more conservative estimate for our ambiguous tokens (70% rather than 50%), these results provide evidence that participants were still accepting of the ambiguous targets as real words to a level that is similar to previous work (e.g., McAuliffe & Babel, 2016; Scharenborg et al., 2015).

[INSERT TABLE 3 NEAR HERE]

Learning Consistent Models

The shift from pretest to posttest was statistically tested using learning consistency (rather than /ɛ/ response) as the dependent variable, such that an increase in learning consistency from the pretest to the posttest represents a shift in the category boundary in the predicted direction. To illustrate the changes in learning-consistent behaviour over the course of the tasks, Figure 3 plots mean learning consistency across pre- and posttest blocks by age and exposure groups for the distributional (3A) and lexically-guided (3B) learning tasks.

Distributional Learning. Table 4 presents the fixed effects estimates from the logistic mixed effects model for the distributional learning data. An increase in learning-consistent behaviour from the pretest to the posttest was confirmed by the main effect of Block (Pre vs. Post: $\beta=0.71$, $z=6.04$, $p<0.001$). The significant effect of Block (Post 1 vs. Post 2-3) with a negative coefficient ($\beta=-0.25$, $z=-2$, $p=0.05$) indicates that there is a decrease in learning consistency after the first block of the posttest. Important to our hypothesis, we find a marginally significant interaction between Age group and Block, which suggests older adults learn less overall (Age group x Block (Pre vs. Posttest): $\beta=0.44$, $z=1.86$, $p=0.06$).

Several other factors in the model were significant but less theoretically interesting. Using learning consistency rather than proportion /ɛ/ as our dependent variable means that we were not expecting a difference in the exposure groups. However, there is a significant effect of Exposure type (the direction of the perceptual shift: /ɛ/-amb vs. /ɪ/-amb) ($\beta= -3.42$, $z= -8.45$, $p<0.001$), which can be seen as the difference between exposure conditions in Figure 3. This seems to be driven by a bias in the data to respond with /ɛ/ (so participants in the /ɛ/ exposure group, for whom an /ɛ/ response is coded as 'consistent', start out with more learning consistent behaviour in the pretest).

[INSERT TABLE 4 & FIGURE 3 NEAR HERE]

Several significant two- and three-way interactions qualify the pattern of learning between the two age and exposure groups across the blocks of the task. The interaction between Exposure type and Block (Post 1 vs. Post 2-3) (β=-1.08, z=-4.39, p<0.001) indicates less unlearning in the /ɛ/-amb exposure group than the /ɪ/-amb exposure group. A significant three-way interaction between Exposure type, Age group, and Block (Post 2 vs. Post 3) indicates that the unlearning was most pronounced for the older adults in the /ɪ/-amb exposure group (β=1.02, z=2.14, p=0.03; Figure 3A).

To summarize the results for the distributional learning task, we find learning from pretest to posttest, weak evidence that older adults might be learning less (marginal significance of Age x Block (Pre vs. Post)), with an /ɛ/-bias that may be influencing the difference between age groups in the unlearning patterns after the initial learning of Posttest block 1.

Lexically-guided Learning. The results from the mixed effects model of learning consistency for the lexically-guided learning data are summarized in Table 5. As with the distributional learning data, there is a significant effect of Block (Pre vs. Post) (β=0.62, z=3.65, p<0.001) again providing evidence for learning from the pretest to the posttest. This time we did not find evidence for different amounts of learning for older and younger adults (i.e., an interaction between Block (Pre vs. Post) and Age group: β=-0.2, z=-0.58, p=0.56).

There were again several other significant effects. We again observed a main effect of Exposure type (β= -3.13, z=-6.46, p<0.001), showing the same bias towards /ɛ/ responses as previously described. It is not surprising that the /ɛ/-bias is present in both tasks, as the same stimuli are used for the pre- and posttests in both tasks, although each participant hears different voices across the two tasks. There is evidence for an increase in learning consistency at the end of the posttest, possibly the result of categorization behaviour stabilizing following unlearning from Block 1 to Block 2 (Block (Post 2 vs. Post 3): $\beta=0.29$, $z=2.26$, $p=0.02$). The significant interaction between Exposure type and Block (Pre vs. Post) ($\beta=0.65$, $z=1.92$, $p=0.05$), suggests that participants in the /ɪ/-amb group show a greater increase in learning-consistent behaviour from the pretest to the posttest than those in the /ɛ/ exposure group. This could be caused by a ceiling effect in the /ɛ/ group, where because they start the pretest already responding frequently with /ɛ/, there is not much room to further increase the number of /ɛ/ responses. This is qualified by a significant three-way interaction between Exposure type, Age group, and Block (Pre vs. Post) ($\beta= -2.25$, $z=-3.31$, $p<0.001$), indicating that older adults show a bigger effect of exposure type in the pretest than younger adults, but both perform similarly in the posttest (i.e., older adults show more of an /ɛ/ bias in the pretest compared to younger adults, but both age groups still show learning; see Figure 3B). In other words, because of the pre-existing /ɛ/ bias, the older adults in the /ɛ/-amb group appear especially learning-consistent in the pretest, while the older adults in the /ɪ/-amb group appear fairly inconsistent. This leaves room for a large increase in learning for the older adults in the /ɪ/ group, but little room for the /ɛ/ group. The younger adults, on the other hand, show less of an /ɛ/ bias at the pretest, and both exposure groups show similar trajectories.

To summarize the lexically-guided learning data, there is a clear learning effect from pre- to posttest, which is again accompanied by the /ɛ/-bias in our data and is likely the reason we find a significant three-way interaction among Exposure type, Age Group, and Block.

[INSERT TABLE 5 NEAR HERE]

To further investigate whether voice and order influence distributional and lexically-guided learning, we ran additional models that included interactions between Task order, Exposure type, and Age group, and between Voice, Exposure type, and Age group (see Appendix B for full model tables). The inclusion of the additional order and voice interactions does not affect the significance of the previously mentioned effects. This provides assurance that the presentation order of the learning tasks does not affect the magnitude of learning in the different groups. However, there are significant interactions with voice. Crucially, there is no interaction with Block, so participants did not learn more when presented with one voice versus the other.

In sum, we find learning from pretest to posttest in both perceptual learning tasks for both age groups. We find a marginal interaction of Age group x Block (Pre vs. Post) in the distributional learning data, and a significant interaction between Exposure type, Age group, and Block (Pre vs. Post) in the lexically-guided learning data, suggesting that there may be some differences in the learning behaviour of the two age groups.

Individual Differences Models

Our last set of analyses investigates the influence of cognitive abilities on perceptual flexibility. We were interested in investigating whether there is a relationship between the amount of perceptual learning for the two tasks, and the cognitive factors that may predict this learning for older adults. To accomplish this, two additional mixed effects logistic regression models were run on the distributional and lexically-guided learning data. To focus on the section of the continuum most likely to demonstrate the shift, only the posttest data on the most ambiguous continuum steps (steps 6, 7, 8) were included in this analysis, as the endpoints should be consistently categorized as either /ɛ/ or /ɪ/. As a measure of each participant's magnitude of learning, the random slopes for Block (Pretest vs. entire Posttest) were extracted from the learning consistency models described above. Random slopes represent an individual's deviance from the fixed effect estimate, thus using the random slope for the first block comparison represents their variation from the mean of pre- versus posttest learning consistency (a positive slope indicates greater than average change from pre- to posttest and a negative slope means a smaller than average change). The random effect slope from the alternate learning task was then used as a predictor of learning consistency in these models (i.e., a participant's lexically-guided random slope for Block was used as a predictor in the distributional learning model, and vice versa). A score of ambiguity acceptance was calculated as the number of ambiguous target words accepted as real words in the lexical decision task (Shift acceptance as in Scharenborg & Janse, 2013), and was standardized and included in the model for individual differences in lexically-guided learning. Additional measures, including PPVT, TMT, SPIN, digit span and PTA, were converted into z-scores around the mean of their respective age group and included in both models. We also included each participant's learning consistent score from the pretest in the models as a fixed effect, as well as their exposure group (/ɪ/ vs. /ɛ/). Again, random slopes by participant were included for all within-subject effects (Continuum step).

Table 6 provides the fixed effects estimates for the distributional learning model of individual differences. Participants' pretest learning consistent score, or in other words, how close their existing category boundary was to the learning-consistent end of the continuum before being exposed to the training phase (e.g., the average pretest responses of /ɛ/ by a participant in the /ɛ/-amb group), significantly predicted their post-test categorization (β=3.64, z=9.37, p<0.001). This is unsurprising, given that individual differences at pretest would be expected to influence posttest categorization. Exposure type was also significant (β=-0.79, z=-

2.55, $p=0.01$), which is reflective of the same response bias mentioned previously. There is a main effect of Age group ($\beta=0.39$, $z=1.96$, $p=0.05$), which provides further evidence that the younger adults are showing more learning-consistent behaviour in the posttest compared to the older adults (Figure 4A). Vocabulary score (PPVT) is also predictive of posttest learning consistency ($\beta=0.81$, $z=2.87$, $p=0.004$), suggesting that participants with larger receptive vocabularies are more learning consistent (Figure 4B). We found no evidence for a relationship between learning in the lexically-guided task (Lexically-guided random slope) and this task.

[INSERT TABLE 6 & FIGURE 4 NEAR HERE]

Table 7 provides the fixed effects estimates for the lexically-guided learning model of individual differences. The effect of Pretest learning consistent score was again significant ($\beta=3.33$, $z=7.93$, $p<0.001$) as was Exposure type ($\beta=-1.18$, $z=-2.89$, $p=0.004$), consistent with the explanation given above for the Distributional learning model. Age group was significant ($\beta=-0.6$, $z=-2.02$, $p=0.04$), but this time in the opposite direction as the effect found for the Distributional learning data, suggesting that older adults show more learning consistent behaviour for the lexically-guided learning task (Figure 5A). Vocabulary score (PPVT) was also significant ($\beta=0.86$, $z=2.42$, $p=0.02$). This provides evidence that larger receptive vocabularies led to more learning-consistent behaviour in lexically-guided learning as well (Figure 5B). We also find a significant interaction between Age group and Shift acceptance ($\beta=1.55$, $z=2.04$, $p=0.04$), suggesting that older adults who are more accepting of ambiguous target items in the exposure phase show less learning-consistent behaviour in the posttest. In sum, vocabulary size, shift acceptance, and age were all predictive of learning in this task, but again, we found no evidence for a relationship between learning in the distributional task (Distributional learning random slope) and this task.

In summary, we found that both younger and older adults showed learning in both perceptual learning tasks, however, older adults may show less learning than younger adults when lexically disambiguating information is unavailable. As noted in our individual differences analysis, we found further support for a difference in the learning behaviour of the two age groups across the two learning tasks. Vocabulary was predictive of learning in both tasks, suggesting an important role for lexical knowledge in perceptual learning.

[INSERT TABLE 7 & FIGURE 5 NEAR HERE]

Discussion

Using two different perceptual learning tasks, we aimed to investigate the importance of lexical status on the magnitude of learning in younger and older adults. Both younger and older adults showed perceptual learning in both lexically-guided learning and distributional learning, however, learning may be weaker for the older adults when compared to the performance of younger adults in the absence of lexically disambiguating information. Only the distributional learning task resulted in a marginal difference between older and younger adults in the overall magnitude of learning (Table 4, Age x Block (Pre vs. Posttest)). While not definitive, this pattern of results is in line with our prediction that a similar magnitude of learning between the older and younger adults in the lexically-guided learning task and (marginally) less learning in the distributional learning task reflects the involvement of the lexicon in maintaining learning for older adults (Figure 2C). Our hypothesis is also supported by the Age group effects found in our individual differences analysis, where we find more learning-consistent behaviour in the older adults compared to younger adults when top-down information is of use and less learning-consistent behaviour in the older adults when it is not.

It should be noted that the design of our distributional learning task is similar to previous work that falls under the realm of selective adaptation (Eimas & Corbit, 1973). In selective adaptation, as in our distributional learning task, individuals are exposed to many good tokens of a given sound and this exposure results in the individual categorizing fewer tokens along a continuum as that sound (e.g., in our case, participants in the /ɛ/-amb group hear good tokens of /ɪ/, and expand the /ɛ/ side of their category while shrinking the /ɪ/ side). Thus both the design and outcomes of these studies are similar, though they are described with different mechanisms. However, there are several studies that show sensitivity to distributional information that cannot be explained by selective adaptation (e.g., Clayards et al., 2008; Idemaru & Holt, 2011; Maye & Gerken, 2000), including in vowels (Liu & Holt, 2015). Thus it remains unclear whether distributional learning can reduce to selective adaptation and indeed, it has been argued that selective adaptation can be explained under the mechanisms of distributional learning (Kleinschmidt & Jaeger, 2015c) rather than the other way around. However, the difference in terminology should not interfere with our main interest of investigating the influence of top-down lexical knowledge in the perceptual learning of older adults. For our purposes, the predictions of selective adaptation and distributional learning are the same.

Overall, the results from our perceptual learning tasks provide further evidence that implicit learning is maintained in aging, as we find learning from pre- to posttest in both learning tasks. We find that when older adults are able to take advantage of top-down knowledge, they show similar learning to younger adults, as in our lexically-guided learning task. When no top-down assistance is available, as in the distributional learning task, implicit learning in older adults may be slightly weakened, given that we find a marginal difference in the learning behaviour between age groups from pretest to posttest and find more learning-consistent behaviour in the younger adults compared to older adults in our individual differences analysis. However, it should be noted when interpreting the individual differences analysis that this does not directly measure an increase in learning consistency from pre- to posttest, although pretest learning consistency is included in the model to account for individual differences at pre-test.

In our investigation of individual differences, we found that only vocabulary size and the acceptance of ambiguous target words predicted performance in either distributional or lexically-guided learning. We did not replicate the findings of Scharenborg et al. (2015) in our full individual differences model. However, in an analysis of only older adult data, we did find an effect of attention-switching control, which suggests that older adults with poorer attention-switching control show more learning-consistent behaviour than those with better attention-switching control. The direction of this attention-switching effect remains consistent with previous work (McAuliffe & Babel, 2016; Scharenborg et al., 2015), suggesting that attending to the signal in a lexically-guided learning task is detrimental to learning compared to maintaining attention at the task-level. We also found differing results from Scharenborg and Janse (2013) in terms of the effect of accepting ambiguous target words on learning-consistent behaviour. Participants who were more accepting of the ambiguous target words actually showed less learning-consistent behaviour during the posttest than those who were less accepting of the ambiguous targets, and this pattern was stronger for older adults.

There were no significant effects found for working memory or for either of our hearing sensitivity measures (PTA and SPIN). This is perhaps unsurprising, as these were the factors that had mixed results in regards to their role in perceptual learning. Our results are in line with the findings of Neger et al. (2014), who also found no effect of working memory on perceptual learning in older adults. It is possible that hearing sensitivity still plays a role in the differences we see between our age groups, given that the older adults do have a significantly higher PTA than the younger adults (although both groups are still within the normal range). The poorer hearing of the older adults may require them to rely more on top-down information to achieve similar learning to the younger adults, and when that information is not available, they show weaker learning compared to younger adults. The differences in learning across tasks may indeed reflect a difference in processing strategies employed by the two age groups. However, it is unclear whether this is born out of necessity due to worsened hearing sensitivity or is a normal change in processing style that comes with age, and given that there is no significant effect in our individual differences analysis, it is likely that hearing sensitivity has little effect on perceptual learning in normal hearing listeners.

Vocabulary size was predictive of learning consistency in both the lexically-guided and distributional learning task. Participants with larger vocabularies showed more learning-consistent behaviour. Similar to the findings of Baese-Berk et al. (2015), where individuals with larger receptive vocabularies performed better at recognizing unfamiliar speech, this relationship could indicate that more lexical knowledge facilitates the plasticity necessary to adapt to ambiguous accents, regardless of the task. Larger receptive vocabularies have been suggested to result in better speech recognition in noise because increased lexical connectivity promotes accessing top-down knowledge (Mattys et al., 2012). In other non-learning speech perception tasks, Ishida, Samuel, and Arai (2016) found that some individuals rely more on top-down lexical information than others, and do so across a variety of speech perception tasks, providing evidence that in young adulthood, some individuals already rely more on top-down information than others. Our finding that vocabulary size enhances perceptual learning in older adults further supports the Scaffolding Theory of Aging and Cognition (Park & Reuter-Lorenz, 2009; Reuter-

Lorenz & Park, 2014), by providing more evidence that additional cognitive processes, like the top-down influence of the lexicon, are recruited for maintaining perceptual learning in older adulthood. In the broader picture of aging, our results are consistent with other findings investigating learning skills in older adulthood. While motor function declines with age, there is evidence that aspects of motor-skill learning are maintained. A review by Voelcker-Rehage (2008) finds that while younger adults show greater improvement in fine motor skills, older adults still show performance gains with practice and differences across age are less evident for gross-motor skills. Furthermore, age effects were found to be harder to detect in simpler motor learning tasks. It is thus impressive that speech learning is maintained to a similar magnitude in our older adult participants when younger adults of our age range often show more learning than older adults in other domains. Because of the age-related declines in motor and cognitive functioning, the Scaffolding Theory of Aging and Cognition (Park & Reuter-Lorenz, 2009; Reuter-Lorenz & Park, 2014) suggests that older adults must recruit additional cortical areas, especially frontal regions, to compensate for the declines in processing efficiency that develop as the neural pathways used in young adulthood begin to degrade with age. Our results fit within this framework, as we provide evidence that while perceptual learning is seemingly maintained in older adults, they likely recruit higher-order processes to show similar flexibility to younger adults, and when no such processes are of use, learning in older adults is slightly impaired.

Given that we find some differences in the learning behaviour of our two age groups, an interesting follow-up to this study would be to control aspects of the learning tasks to make them more similar, with the goal of isolating the presence of lexically disambiguating information as the sole difference between the tasks. We attempted this by designing our distributional learning experiment to be similar to our lexically-guided learning experiment, however, learning in our distributional learning experiment was still slower and required more trials than our lexically-guided learning experiment (528 test trials in the distributional task versus 200 exposure trials – 20 of which are test trials – in the lexically-guided task). A recent study (Chládková, Podlipský, & Chionidou, 2017) manipulated lexical status within a lexically-guided learning experiment, whereby the ambiguous vowel appeared in either real words or in a phonotactically-permissable context in a nonword. In contrast to earlier studies (e.g., Norris et al., 2003), learning was found in both word and nonword contexts, suggesting that perceptual learning is possible with little exposure (in Chládková et al., 2017, 64 target nonword trials, 160 exposure trials total) even in the absence of lexically disambiguating information. Using a similar design with older adult participants would be interesting to further investigate the role of top-down information in maintaining perceptual learning.

Conclusion

Plasticity for speech is maintained with aging, but it may be affected by the information that is available to the listener, as older adults may rely more on lexical knowledge to achieve similar performance to younger adults. We aimed to investigate the role of the lexicon in the perceptual learning of older adults, and found that older adults do seem to show more learning when top-down information is available compared to when it is absent. The differences found here between the age groups across blocks may be related to the different strategies employed by younger and older adults. Older adults are known to have increased lexical biases during speech perception (Mattys & Scharenborg, 2014, for example) and to utilize lexical knowledge to their advantage to successfully recognize speech. Lexical knowledge, as reflected here by a receptive vocabulary measure, was found to influence perceptual learning across both age groups, providing further support for the importance of top-down processes in this type of flexibility.

Despite noted difficulties in speech perception, older adults remain perceptually flexible in both types of learning tasks.

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Tables.

Table 1.

Order of tasks by session.

Session A	Session B
Distributional Learning task	Lexical Learning task
	SPIN
	TMT
	Backward Digit Span
	PPVT

Table 2.

Counterbalancing of learning tasks. "?" indicates ambiguous stimulus.

	1st Session			2nd Session		
Order	Task	Voice	Ambiguous Condition	Task	Voice	Ambiguous Condition
A	Lexically-guided	Male	/ɛ/: ups?t – violin	Distributional	Female	/ɪ/: pen – p?n
B			/ɪ/: upset – viol?n			/ɛ/: p?n – pin
C		Female	/ɛ/: ups?t – violin		Male	/ɪ/: pen – p?n
D			/ɪ/: upset – viol?n			/ɛ/: p?n – pin
E	Distributional	Male	/ɛ/: p?n – pin	Lexically-guided	Female	/ɪ/: upset – viol?n
F			/ɪ/: pen – p?n			/ɛ/: ups?t – violin
G		Female	/ɛ/: p?n – pin		Male	/ɪ/: upset – viol?n
H			/ɪ/: pen – p?n			/ɛ/: ups?t – violin

Table 3.

Mean percentage correct ('yes' response) for the target /ɛ/ and /ɪ/ words in the lexical decision task.

Age Group	Clear targets		Ambiguous targets	
	/ɛ/	/ɪ/	/ɛ/	/ɪ/
Younger	95.3	96.2	82.5	91.5
Older	96.4	96.1	91.1	87.1

Table 4.

Fixed effects estimates from a model of distributional learning consistency.

Fixed effect	Estimate	Std. Error	z value	p	
Intercept	0.29	0.2	1.43	0.15	
Continuum Step	7.68	0.35	22.14	<0.001	***
Block (pre vs. post)	0.71	0.12	6.04	<0.001	***
Block (post 1 vs. post 2-3)	-0.25	0.12	-2.00	0.05	*
Block (post 2 vs. post 3)	-0.1	0.12	-0.85	0.39	
Exposure type	-3.42	0.4	-8.45	<0.001	***
Age group	0.17	0.4	0.43	0.67	
Exposure type x Block (pre vs. post)	-0.19	0.24	-0.81	0.42	
Exposure type x Block (post 1 vs. post 2-3)	-1.08	0.25	-4.39	<0.001	***
Exposure type x Block (post 2 vs. post 3)	0.08	0.24	0.33	0.74	
Age group x Block (pre vs. post)	0.44	0.24	1.86	0.06	.
Age group x Block (post 1 vs. post 2-3)	-0.33	0.25	-1.35	0.18	
Age group x Block (post 2 vs. post 3)	0.42	0.24	1.77	0.08	
Exposure type x Age group	1.39	0.8	1.73	0.08	
Exposure type x Age group x Block (pre vs. post)	-0.26	0.47	-0.55	0.58	
Exposure type x Age group x Block (post 1 vs. post 2-3)	0.62	0.49	1.26	0.21	
Exposure type x Age group x Block (post 2 vs. post 3)	1.02	0.47	2.14	0.03	*

Table 5.

Fixed effects estimates from a model of lexically-guided learning consistency.

Fixed Effect	Estimate	Std. Error	z value	p	
Intercept	-0.02	0.24	-0.07	0.95	
Continuum step	8.55	0.43	19.66	<0.001	***
Block (Pre vs. Post)	0.62	0.17	3.65	<0.001	***
Block (Post 1 vs. Post 2-3)	-0.13	0.15	-0.86	0.39	
Block (Post 2 vs. Post 3)	0.29	0.13	2.26	0.02	*
Exposure type	-3.13	0.48	-6.46	<0.001	***
Age group	-0.57	0.48	-1.18	0.24	
Exposure type x Block (Pre vs. Post)	0.65	0.34	1.92	0.05	*
Exposure type x Block (Post 1 vs. Post 2-3)	0.01	0.3	0.05	0.96	
Exposure type x Block (Post 2 vs. Post 3)	-0.01	0.26	-0.06	0.96	
Age group x Block (Pre vs. Post)	-0.2	0.34	-0.58	0.56	
Age group x Block (Post 1 vs. Post 2-3)	0.23	0.3	0.78	0.44	
Age group x Block (Post 2 vs. Post 3)	-0.1	0.26	-0.41	0.68	
Exposure type x Age group	0.83	0.96	0.86	0.39	
Exposure type x Age group x Block (Pre vs. Post)	-2.25	0.68	-3.31	0.001	***
Exposure type x Age group x Block (Post 1 vs. Post 2-3)	-0.86	0.59	-1.45	0.15	
Exposure type x Age group x Block (Post 2 vs. Post 3)	0.54	0.51	1.06	0.29	

Table 6.

Fixed effects estimates from a model of individual differences in distributional learning.

Fixed Effect	Estimate	Std. Error	z value	p	
Intercept	0.57	0.11	5.08	<0.001	***
Continuum step	6.95	0.63	11.1	<0.001	***
Age group	0.39	0.23	1.96	0.05	*
Exposure type	-0.79	0.31	-2.55	0.01	**
Pretest LC score	3.64	0.39	9.37	<0.001	***
Lexically-guided random slope	-0.04	0.27	-0.16	0.87	
PPVT	0.81	0.28	2.87	0.004	**
TMT	-0.07	0.27	-0.26	0.79	
Digit span	-0.02	0.26	-0.06	0.95	
PTA	0.52	0.30	1.72	0.08	
SPIN difference score	0.31	0.23	1.34	0.18	
Continuum step x Age group	-0.03	1.24	-0.03	0.98	
Exposure type x Age group	0.26	0.62	0.41	0.68	
Pretest LC score x Age group	0.03	0.77	0.04	0.97	
L-G Random slope x Age group	0.68	0.53	1.28	0.20	
PPVT x Age group	0.41	0.57	0.72	0.47	
TMT x Age group	0.15	0.55	0.28	0.78	
Digit span x Age group	-0.91	0.52	-1.77	0.08	
PTA x Age group	-0.92	0.61	-1.50	0.13	
SPIN diff. score x Age group	-0.27	0.47	-0.58	0.56	

Table 7.

Fixed effects estimates from a model of individual differences in lexically-guided learning.

Fixed effect	Estimate	Std. Error	z value	p	
Intercept	0.24	0.15	1.64	0.1	
Continuum step	8.63	0.69	12.48	<0.001	***
Age group	-0.6	0.29	-2.02	0.04	*
Exposure type	-1.18	0.41	-2.89	0.004	**
Pretest LC score	3.33	0.42	7.93	<0.001	***
Dist. Learning random slope	0.34	0.36	0.95	0.34	
PPVT	0.86	0.35	2.42	0.02	*
TMT	0.33	0.35	0.95	0.34	
Shift acceptance	-0.56	0.37	-1.51	0.13	
Digit span	-0.5	0.35	-1.42	0.16	
PTA	-0.08	0.41	-0.19	0.85	
SPIN difference score	0.17	0.3	0.56	0.58	
Continuum step x Age group	-2.45	1.35	-1.82	0.07	
Exposure type x Age group	-0.69	0.82	-0.84	0.4	
Pretest LC score x Age group	0.06	0.83	0.07	0.94	
Dist. Learning rand. slope x Age group	0.51	0.72	0.71	0.48	
PPVT x Age group	-1.09	0.7	-1.56	0.12	
TMT x Age group	-1	0.71	-1.42	0.16	
Shift acceptance x Age group	1.55	0.76	2.04	0.04	*
Digit span x Age group	0.13	0.7	0.19	0.85	
PTA x Age group	0.28	0.83	0.33	0.74	
SPIN diff. score x Age group	0.99	0.61	1.63	0.10	

Figures.

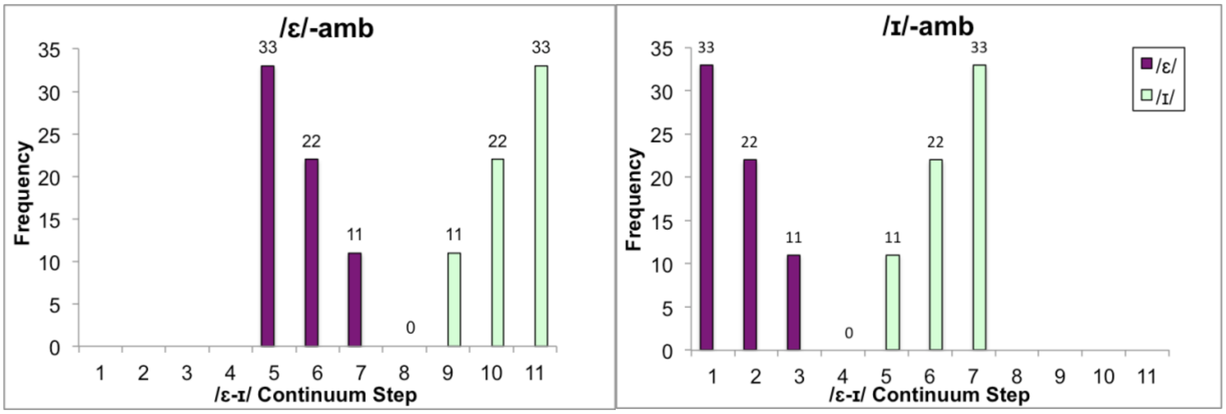

Figure 1. The two exposure distributions for a block of the distributional learning task. Following exposure, the shifted boundary is expected to move towards step 8 or step 4, for /ɛ/-amb and /ɪ/-amb groups respectively.

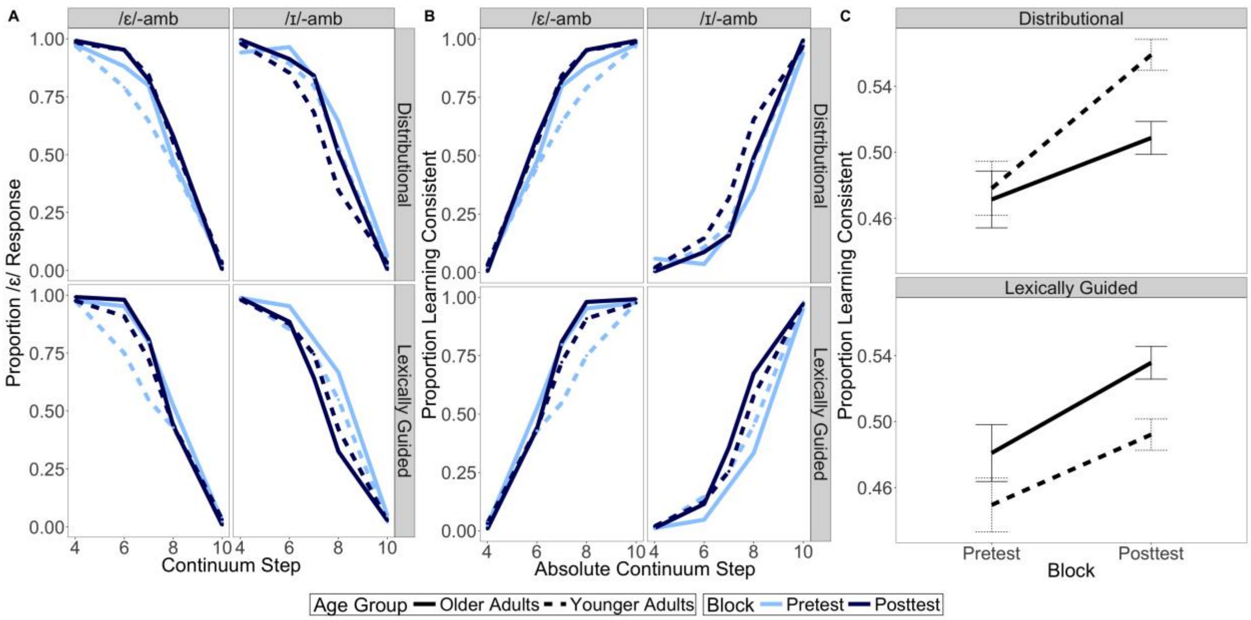

Figure 2. Pre- and posttest categorization responses for the distributional learning task (top row) and the lexically-guided learning task (bottom row), presented as (a) proportion /ɛ/ responses, (b) proportion learning consistent responses, and (c) proportion learning consistent responses averaged across continuum steps.

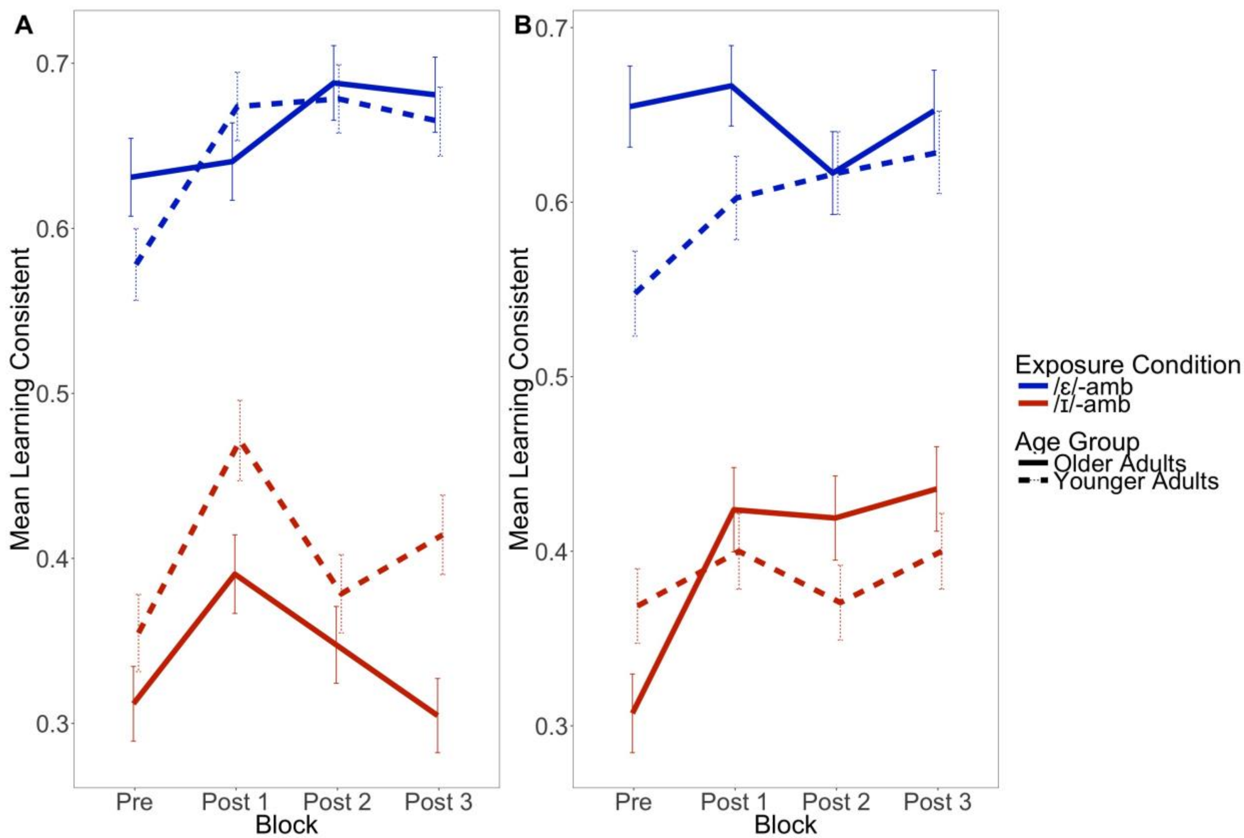

Figure 3. Mean learning consistent behaviour by Age group, Exposure type, and Block for (a) Distributional learning task and (b) Lexically-guided learning task. Error bars represent standard error of the mean.

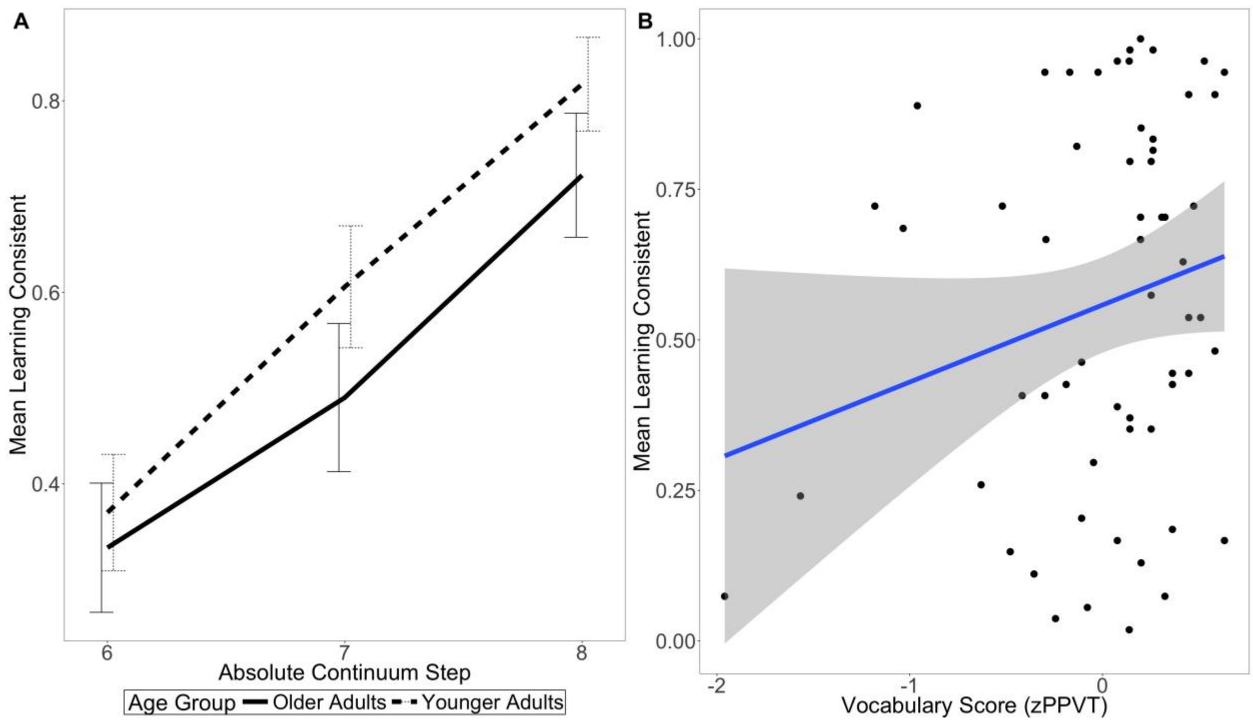

Figure 4[1]. Significant predictors of learning consistency in distributional learning: (a) effect of Age group, (b) effect of vocabulary size.

[1] Despite the appearance of outliers in Figure 4B, the effects remain significant when the outliers (the two participants with the lowest PPVT scores) are excluded from the analysis.

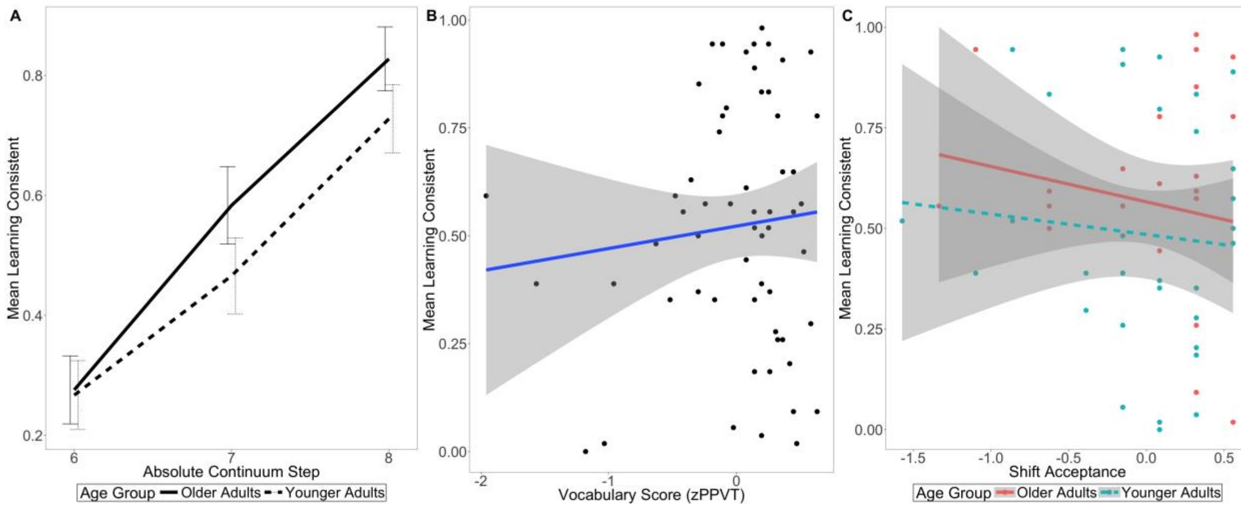

Figure 5[2]. Significant predictors of learning consistency in lexically-guided learning: (a) effect of Age group, (b) effect of vocabulary size, and (c) effect of shift acceptance.

[2] Despite the appearance of outliers in Figure 5B, the effects remain significant when the outliers (the two participants with the lowest PPVT scores) are excluded from the analysis.

Appendix A

List of stimuli for perceptual learning tasks

Table A1.

Words for the lexically-guided learning task.

/ɪ/ words	/ɛ/ words	Fillers	Nonwords		*
zip	wed	cat	jat	salvore	*silver*
stitch	mesh	boot	koom	peerfut	*perfect*
fin	hen	road	roaf	gromaitch	*donate*
lip	lend	stop	stod	transawss	*princess*
brick	less	sheep	geep	strogy	*broken*
kit	chest	man	maf	tookar	*sugar*
click	dress	suit	stoon	volan	*woman*
whip	depth	mop	rop	sathen	*father*
fish	vest	teal	leet	prubby	*money*
hitch	shred	file	kife	nomspen	*monster*
bridge	stress	bowl	bom	bothag	*nothing*
dish	nest	cup	tup	dountage	*mountain*
unstick	address	right	dite	sarcoot	*circus*
refill	arrest	key	kai	drynoss	*kindness*
fulfill	digest	odd	oss	tunpad	*football*
uphill	refresh	band	chand	shreetur	*treasure*
until	object	book	bup	morast	*forest*
admit	upset	shoe	shoon	rapty	*pasta*
submit	attend	sly	slee	pimant	*silence*
violin	acquiesce	shape	lape	thuppen	*bucket*
		turtle	tarkle	damynel	*animal*
		follow	sowo	tattirass	*happiness*
		surprise	thurprife	choodoplay	*chipotle*
		island	allard	mabricole	*abdicate*
		bacon	kabon	maderige	*favourite*
		avoid	assoin	ploreefa	*forever*
		hockey	lommy	raspony	*history*
		pizza	tissa	hadrentut	*adventure*
		people	beekle	fyblable	*syllable*
		future	shubure	krugathem	*together*
		country	tuntly	moshulen	*pollution*
		freedom	fradon	brazeemen	*president*
		fourteen	mourteesh	garentai	*calendar*
		provoke	trovope	hadgitock	*adjective*
		thousand	powkand	wadgerod	*withering*

Fillers	Nonwords		*
pirate	kirad	myniseen	*medicine*
away	arru	cromacon	*convection*
journey	joongy	shunlarite	*cleanliness*
story	skoly	navolla	*vanilla*
season	feavon	chalprocol	*alcohol*
consonant	bonfonank		
banana	parama		
piano	diamie		
potato	gopago		
media	neepeeo		
period	deeliot		
company	pomdamy		
abacus	amatuk		
tomorrow	sorommow		
xylophone	syrodote		
crocodile	trodolime		
casino	gamiso		
dinosaur	pimolaur		
volcano	dolparo		
stadium	traziun		
agony	aboly		
galaxy	pamatry		
savanna	famazza		
trampoline	prastorime		
colony	boromy		

* English word used to create nonwords; the first column of nonwords is based on the fillers

Table A2.

Words for the distributional learning task.

Minimal pairs	
bid	bed
pit	pet
tin	ten
pick	peck
pin*	pen*
tick	tech
nick	neck
miss	mess
gym	gem
sit	set
mitt	met
knit	net

*After piloting, pen-pin was excluded from the exposure phase.

Appendix B.

Additional model results investigating interaction effects of Voice and Order.

Table B1.

Fixed effects estimates from a model investigating interactions of Order on learning consistency in the distributional learning task.

Fixed Effect	Estimate	Std. Error	z value	p	
Intercept	0.29	0.2	1.48	0.14	
Continuum step	-7.69	0.35	-22.1	<0.001	***
Order	-0.04	0.4	-0.09	0.93	
Block (Pre vs. Post)	0.7	0.12	6.08	<0.001	***
Block (Post 1 vs. Post 2-3)	-0.25	0.12	-2.03	0.04	*
Block (Post 2 vs. Post 3)	-0.09	0.12	-0.75	0.45	
Exposure type	-3.42	0.4	-8.48	<0.001	***
Age Group	0.22	0.4	0.54	0.58	
Order x Block (Pre vs. Post)	0.18	0.23	0.77	0.44	
Order x Block (Post 1 vs. Post 2-3)	0.07	0.25	0.3	0.76	
Order x Block (Post 2 vs. Post 3)	0.13	0.24	0.53	0.59	
Order x Exposure type	-0.69	0.8	-0.86	0.39	
Exposure Type x Block (Pre vs. Post)	-0.2	0.23	-0.84	0.39	
Exposure Type x Block (Post 1 vs Post 2-3)	-1.08	0.25	-4.4	<0.001	***
Exposure Type x Block (Post 2 vs. Post 3)	0.06	0.24	0.26	0.79	
Age Group x Block (Pre vs. Post)	0.37	0.23	1.59	0.11	
Age Group x Block (Post 1 vs. Post 2-3)	-0.36	0.25	-1.44	0.14	
Age Group x Block (Post 2 vs. Post 3)	0.42	0.24	1.76	0.08	
Age Group x Exposure Type	1.47	0.81	1.83	0.06	.
Order x Block (Pre vs. Post) x Exposure type	0.77	0.47	1.64	0.1	
Order x Block (Post 1 vs. Post 2-3) x Exposure type	0.33	0.5	0.67	0.50	
Order x Block (Post 2 vs. Post 3) x Exposure type	-0.4	0.48	-0.84	0.40	
Block (Pre vs. Post) x Age group x Exposure type	-0.4	0.47	-0.85	0.39	
Block (Post 1 vs. Post 2-3) x Age group x Exposure type	0.56	0.5	1.13	0.25	
Block (Post 2 vs. Post 3) x Age group x Exposure type	1.05	0.48	2.17	0.03	*

Table B2.

Fixed effects estimates from a model investigating interactions of Order on learning consistency in the lexically-guided learning task.

Fixed Effect	Estimate	Std. Error	z value	p	
Intercept	0	0.24	-0.02	0.98	
Continuum step	-8.55	0.43	-19.68	<0.001	***
Order	0.25	0.48	0.53	0.6	
Block (Pre vs. Post)	0.61	0.17	3.6	<0.001	***
Block (Post 1 vs. Post 2-3)	-0.14	0.14	-0.94	0.34	
Block (Post 2 vs. Post 3)	0.28	0.13	2.17	0.03	*
Exposure type	3.11	0.48	6.48	<0.001	***
Age group	-0.55	0.48	-1.14	0.26	
Order x Block (Pre vs. Post)	-0.09	0.34	-0.26	0.8	
Order x Block (Post 1 vs. Post 2-3)	-0.39	0.29	-1.33	0.18	
Order x Block (Post 2 vs. Post 3)	0.22	0.26	0.87	0.38	
Order x Exposure type	-0.74	0.96	-0.76	0.44	
Exposure Type x Block (Pre vs. Post)	-0.65	0.34	-1.93	0.05	*
Exposure Type x Block (Post 1 vs Post 2-3)	0.01	0.29	0.04	0.97	
Exposure Type x Block (Post 2 vs. Post 3)	-0.01	0.25	-0.04	0.97	
Age Group x Block (Pre vs. Post)	-0.23	0.34	-0.66	0.51	
Age Group x Block (Post 1 vs. Post 2-3)	0.24	0.29	0.83	0.41	
Age Group x Block (Post 2 vs. Post 3)	-0.16	0.26	-0.64	0.52	
Age Group x Exposure Type	-0.81	0.96	-0.84	0.40	
Order x Block (Pre vs. Post) x Exposure type	0.65	0.68	0.94	0.35	
Order x Block (Post 1 vs. Post 2-3) x Exposure type	0.62	0.59	1.05	0.29	
Order x Block (Post 2 vs. Post 3) x Exposure type	0.61	0.51	1.19	0.23	
Block (Pre vs. Post) x Age group x Exposure type	2.19	0.68	3.2	0.001	***
Block (Post 1 vs. Post 2-3) x Age group x Exposure type	0.87	0.59	1.48	0.14	
Block (Post 2 vs. Post 3) x Age group x Exposure type	-0.67	0.51	-1.31	0.19	

Table B3.

Fixed effects estimates from a model investigating interactions of Voice on learning consistency in the distributional learning task.

Fixed Effect	Estimate	Std. Error	z value	p	
Intercept	0.3	0.15	1.96	0.05	
Continuum step	-7.64	0.34	-22.63	<0.001	***
Block (Pre vs. Post)	0.71	0.12	6.09	<0.001	***
Block (Post 1 vs. Post 2-3)	-0.24	0.12	-1.94	0.05	*
Block (Post 2 vs. Post 3)	-0.12	0.12	-0.99	0.32	
Exposure type	-3.31	0.31	-10.59	<0.001	***
Voice	0.34	0.31	1.12	0.26	
Age Group	0.07	0.31	0.24	0.81	
Exposure type x Block (Pre vs. Post)	-0.19	0.23	-0.81	0.42	
Exposure type x Block (Post 1 vs. Post 2-3)	-1.09	0.25	-4.44	<0.001	***
Exposure type x Block (Post 2 vs. Post 3)	0.12	0.24	0.5	0.62	
Voice x Block (Pre vs. Post)	-0.34	0.23	-1.45	0.14	
Voice x Block (Post 1 vs. Post 2-3)	0.13	0.25	0.52	0.60	
Voice x Block (Post 2 vs. Post 3)	-0.06	0.24	-0.24	0.81	
Voice x Expoure type	-3.8	0.62	-6.17	<0.001	***
Age group x Block (Pre vs. Post)	0.45	0.23	1.94	0.05	*
Age group x Block (Post 1 vs. Post 2-3)	-0.35	0.25	-1.41	0.16	
Age group x Block (Post 2 vs. Post 3)	0.45	0.24	1.88	0.06	
Age group x Exposure type	1.34	0.62	2.17	0.03	*
Voice x Exposure type x Block (Pre vs. Post)	-0.04	0.46	-0.08	0.94	
Voice x Exposure type x Block (Post 1 vs. Post 2-3)	-0.19	0.49	-0.4	0.69	
Voice x Exposure type x Block (Post 2 vs. Post 3)	0.82	0.47	1.73	0.08	
Age group x Exposure type x Block (Pre vs. Post)	-0.31	0.46	-0.67	0.50	
Age group x Exposure type x Block (Post 1 vs. Post 2-3)	0.64	0.49	1.29	0.19	
Age group x Exposure type x Block (Post 2 vs. Post 3)	0.96	0.48	2.02	0.04	*

Table B4.

Fixed effects estimates from a model investigating interactions of Voice on learning consistency in the lexically-guided learning task.

Fixed Effect	Estimate	Std. Error	z value	p	
Intercept	-0.01	0.19	-0.05	0.96	
Continuum step	-8.5	0.42	-20.08	<0.001	***
Block (Pre vs. Post)	0.61	0.17	3.66	<0.001	***
Block (Post 1 vs. Post 2-3)	-0.11	0.15	-0.75	0.45	
Block (Post 2 vs. Post 3)	0.31	0.13	2.39	0.02	*
Exposure type	3.21	0.39	8.15	<0.001	***
Voice	-0.34	0.39	-0.86	0.39	
Age Group	-0.65	0.39	-1.68	0.09	
Exposure type x Block (Pre vs. Post)	-0.69	0.33	-2.07	0.04	*
Exposure type x Block (Post 1 vs. Post 2-3)	0	0.29	0.01	0.99	
Exposure type x Block (Post 2 vs. Post 3)	0.02	0.25	0.07	0.94	
Voice x Block (Pre vs. Post)	-0.2	0.33	-0.61	0.54	
Voice x Block (Post 1 vs. Post 2-3)	0.32	0.29	1.09	0.27	
Voice x Block (Post 2 vs. Post 3)	0.27	0.25	1.05	0.29	
Voice x Expoure type	4.26	0.78	5.45	<0.001	***
Age group x Block (Pre vs. Post)	-0.17	0.33	-0.51	0.61	
Age group x Block (Post 1 vs. Post 2-3)	0.22	0.29	0.76	0.45	
Age group x Block (Post 2 vs. Post 3)	-0.09	0.25	-0.36	0.72	
Age group x Exposure type	-0.86	0.78	-1.11	0.27	
Voice x Exposure type x Block (Pre vs. Post)	-1	0.67	-1.49	0.14	
Voice x Exposure type x Block (Post 1 vs. Post 2-3)	0.19	0.59	0.33	0.74	
Voice x Exposure type x Block (Post 2 vs. Post 3)	-0.05	0.51	-0.1	0.92	
Age group x Exposure type x Block (Pre vs. Post)	2.29	0.67	3.42	0.001	***
Age group x Exposure type x Block (Post 1 vs. Post 2-3)	0.81	0.59	1.38	0.17	
Age group x Exposure type x Block (Post 2 vs. Post 3)	-0.58	0.51	-1.14	0.25	