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BRIEF REPORT

Aging and the Statistical Learning of Grammatical Form Classes

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Language learners must place unfamiliar words into categories, often with few explicit indicators about when and how that word can be used grammatically. Reeder, Newport, and Aslin (2013) showed that college students can learn grammatical form classes from an artificial language by relying solely on distributional information (i.e., contextual cues in the input). Here, 2 experiments revealed that healthy older adults also show such statistical learning, though they are poorer than young at distinguishing grammatical from ungrammatical strings. This finding expands knowledge of which aspects of learning vary with aging, with potential implications for second language learning in late adulthood.

Keywords: aging, statistical learning, language

Our environment is regular, from the routines of daily life to the (partially) predictable behaviors of the familiar people around us. *Statistical learning* refers to the domain-general capacity to learn these regularities, without intention or often even conscious awareness (e.g., Fiser & Aslin, 2001; Reber, 1967; Saffran, Aslin, & Newport, 1996; Turk-Browne, Scholl, Chun, & Johnson, 2009). Statistical learning is essential throughout life, because it enables us to adapt to new environments, routines, and people (e.g., Turk-Browne, 2012).

Statistical learning plays an important role in first language acquisition (Aslin & Newport, 2014), and there is evidence that it is also involved in second language learning in adults (Ettlinger, Morgan-Short, Faretta-Stutenberg, & Wong, 2015). Yet relatively little is known about the influence of healthy aging on statistical learning abilities. Age-related deficits have been reported in a recent life span study by Lukács and Kemény (2015) in which participants listened to linguistic stimuli that—unbeknownst to them—followed an artificial grammar (drawn from Saffran, 2002). On a subsequent test, all groups showed above-chance discrimination between grammatical and ungrammatical sequences, except people over the age of 65. Other studies of statistical learning have reported mixed findings regarding age-related deficits, perhaps due to differences in the types of stimuli, the presentation modality, and the nature of the regularity, as well as in how and when learning was assessed (e.g., Campbell, Zimerman, Healey, Lee, & Hasher, 2012; Midford & Kirsner, 2005; Neger, Rietveld, & Janse, 2014).

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Here we examine whether there are adult age differences in the statistical learning of grammatical form classes. This is a central problem facing language learners: When should a word be considered to belong to a known grammatical category (e.g., verb, noun, adjective) and when should it be treated as novel and lexically distinct (Mintz, 2002; Reeder, Newport, & Aslin, 2013)?

The *distributional learning hypothesis* argues that people use statistical learning to acquire grammatical categories from the structure of input (i.e., the contextual information surrounding a word; Cartwright & Brent, 1997; Mintz, Newport, & Bever, 1995, 2002; Mintz, 2002, 2003; Reeder et al., 2013). Mintz (2002) showed that college-aged participants exposed to an artificial language were able to organize words into grammatical form classes based solely on distributional information. Further, Reeder et al. (2013) found that learners organize words into categories based on the degree to which the surrounding linguistic contexts for those words overlap. That is, learners are highly sensitive to the number of lexical contexts a given word shares with other category members (overlap) and the probability with which they hear (or fail to hear) each word-context combination.

The present study extends Reeder et al. (2013) to compare statistical learning of grammatical categories from distributional information alone in young (19 to 24) and older (65 and over) adults. Using one of the artificial language designs from Reeder et al., we conducted two experiments—using different acquisition conditions and test instructions—to maximize the possibility that older adults are performing at their best. In Experiment 1, learning occurred as part of an attention-grabbing interactive game and was tested via recognition ratings. In contrast, in Experiment 2, learning occurred through passive exposure and was tested via grammaticality ratings. We expected older adults would learn significantly less than young in both experiments, and Lukács and Kemény's (2015) results raised the possibility that the older adults might not learn at all.

Method

Participants

A total of 80 monolingual, native English speakers participated, with 20 young and 20 old in each experiment (see Table 1). Participants in each group and experiment were randomly assigned to Language 1 or 2, as described below. Young participants were recruited by flyers around Georgetown University and older by newspaper advertisements.

Stimulus Materials

The artificial language task used here was developed by Reeder et al. (2013). The grammar had the structure (Q)AXB(R), where each letter represents a category of nonsense words: "X" represents the target grammatical form class category, "A" and "B" represent the context categories (i.e., the distributional cues surrounding X), and "Q" and "R" were optional flanker categories used to vary the length of strings between three and five words. The Q and R categories contained two words each, the A and B categories had three words each, and the X category had four. The words for both languages were *spad*, *klidum*, *flairb*, *daffin*, *glim*, *tomber*, *zub*, *lapal*, *fluggit*, *mawg*, *bleggin*, *gentif*, and *frag*; the languages differed only in which of the words was assigned to each category (see Table 2 for examples).

Following Reeder et al. (2013, Experiment 2) an exposure set was constructed using nine of the 27 possible combinations of the AXB strings combined with the optional Q and R flanker words. Importantly, the nine AXB strings were selected such that every "X" word was heard in the context of every "A" word and every "B" word (though not every "A_B" context; some of the latter were omitted in order to test generalization to new AXB strings). As mentioned in the Introduction, learners organize words into categories based on the degree to which the surrounding linguistic contexts for those words overlap (Reeder et al., 2013). Based on this exposure corpus, in which "X" words have completely overlapping contexts, learners should organize them into a single category. The exposure set had 36 (Q)AXB(R) strings, each presented four times[1] in one of six orders selected randomly for each participant. A 54-item test set was also constructed consisting of three types of three-word test strings (e.g., *glim zub mawg*): *grammatical familiar* (nine AXB strings presented during exposure, each tested twice), *grammatical novel* (nine AXB strings that were withheld during exposure, each tested twice), and *ungrammatical* (18 unique strings in the form of AXA or BXB, with each string made up of two different "A" or "B" words).[2]

Procedure

In a 25-min session, individual participants completed signed consent and a biographical questionnaire before listening to their exposure set for approximately 12 min.

In Experiment 1, exposure consisted of a "game" in which participants listened to an alien saying sentences in a new language: "Listen carefully while Zooma practices [a language called SillySpeak.] When she arrives on her new planet, she is going to say some more Sillyspeak sentences. Your job will be to decide if you have heard Zooma say that sentence before." While listening, participants watched the alien move around the screen. To ensure attention, the game also included a detection task; when the alien repeated a sentence twice in a row, it stopped, and participants had to click to continue. In contrast, in Experiment 2, during exposure, participants watched a blank black screen and were told that they would hear sentences from an unfamiliar language, "All you have to do for this part of the experiment is listen to the sentences. Try to pay attention to them, because you will be tested on your memory of them later."

Following exposure, the experimenter read aloud on-screen instructions for the test phase. In Experiment 1, participants rated each test string on a scale of 1 to 5, reflecting their confidence that they had heard the alien say that sentence, with "1" indicating that they definitely did not hear that sentence, and "5" that they definitely did. In Experiment 2, they rated their confidence that each string came from the language they were exposed to, with

[1] The exposure set also included one novel word (present in four additional sentence strings) that was not included in the present analyses, for a total of 40 sentences.

[2] For more details on construction of the artificial language, see Reeder et al. (2013) section 3.1.2 (p. 39), Table 1, Table 2, and Supplementary Table 2.

Table 1
Demographic Information for Younger and Older Adults in Experiments 1 and 2

	Experiment 1			Experiment 2		
Demographic	Younger adult means	Older adult means	*t* value	Younger adult means	Older adult means	*t* value
Age (years)	21.3 (1.6)	73.6 (5.6)	—	20.9 (1.6)	70.2 (4.9)	—
Education (years)	14.9 (1.1)	17.2 (2.1)	4.33*	14.8 (1.2)	18.0 (3.2)	4.13*
NAART-35[a]	11.3 (6.1)	8.3 (6.1)	1.55	12.3 (5.5)	9.3 (6.8)	1.52
BDS	7.95 (2.4)	7.3 (1.7)	1.00	8.3 (2.7)	6.4 (2.0)	2.49*
MMSE	—	28.7 (1.4)	—	—	29.1 (1.3)	—
Self-reported health (1–5)	4.9 (.4)	4.4 (.7)	2.60*	4.7 (.4)	4.3 (1.0)	1.20
Gender: males/females (*n*)	7/13	7/13	—	7/13	11/9	—

Note. Standard deviations are in parentheses. *t* value column shows results of independent samples *t*-tests between younger and older adult means. NAART-35 = North American Adult Reading Test-35 (Uttl, 2002); BDS = Backward Digit Span (Wechsler, 1997); MMSE = Mini Mental State Examination (Folstein, Folstein, & McHugh, 1975).
[a] Higher scores reflect worse performance (for all other tests, higher scores reflect better performance).
* Younger and older adults' means differ significantly ($p < .05$).

"1" indicating that it definitely did not, and "5" that it definitely did (following Reeder et al., 2013).

Results

To adjust for possible differences in the way people used the rating scale, we calculated z-scores of sentence ratings for each participant. Separate mixed-design 2 × 2 × 3 analyses of variance (ANOVAs) with age and language (1 or 2) as between-subjects factors and string type (grammatical familiar, grammatical novel, and ungrammatical) as a within-subjects factor revealed an identical pattern for the two experiments. As seen in Figure 1, there was a significant main effect of string type: Experiment. 1, $F(2, 72) = 72.079$, $p < .0001$, $\eta_p^2 = .67$; Experiment 2, $F(2, 72) = 39.87$, $p < .0001$, $\eta_p^2 = .53$, and a significant String Type × Age interaction: Experiment 1, $F(2, 72) = 12.061$, $p < .0001$, $\eta_p^2 = .25$; Experiment 2, $F(2, 72) = 6.14$, $p = .003$, $\eta_p^2 = .15$. No other main effects or interactions approached significance.[3]

Table 2
Example Stimuli for Each of the Two Artificial Languages (1 and 2), Including the 9 AXB Strings (and Optional Q and R Flanker Words) Presented During Exposure, As Well As Possible Grammatical Familiar, Grammatical Novel, and Ungrammatical Strings Presented at Test

(Q)	A	X	B	(R)
		Language 1		
(frag)	gentif	spad	glim	(lapal)
(daffin)	gentif	bleggin	zub	(flairb)
	gentif	fluggit	tomber	
	mawg	fluggit	zub	
	mawg	bleggin	glim	
	mawg	spad	tomber	
	klidum	bleggin	tomber	
	klidum	fluggit	glim	
	klidum	spad	zub	
		Grammatical familiar example: klidum spad zub *Grammatical novel example:* gentif bleggin glim *Ungrammatical example:* mawg fluggit klidum		
		Language 2		
(spad)	flairb	tomber	fluggit	(gentif)
(klidum)	flairb	zub	mawg	(frag)
	flairb	lapal	bleggin	
	daffin	lapal	mawg	
	daffin	zub	fluggit	
	daffin	tomber	bleggin	
	glim	zub	tomber	
	glim	lapal	bleggin	
	glim	tomber	mawg	
		Grammatical familiar example: daffin lapal mawg *Grammatical novel example:* flairb zub fluggit *Ungrammatical example:* glim lapal daffin		

Post hoc paired samples *t* tests revealed that for both age groups, grammatical novel and grammatical familiar strings did not differ from each other: young, Experiment 1, $t(19) = .167$, $p = .869$, and Experiment 2, $t(19) = .171$, $p = .198$; old, Experiment 1, $t(19) = .550$, $p = .59$, and Experiment 2, $t(19) = .691$, $p = .498$. However, the grammatical strings were rated significantly higher than ungrammatical strings for both ages: young, Experiment 1, $t(19) = 9.22$, $p < .001$, and Experiment. 2, $t(19) = 5.92$, $p < .001$; old, Experiment 1, $t(19) = 4.83$, $p < .001$, and Experiment 2, $t(19) = 3.32$, $p = .004$. Further, this difference between grammatical and ungrammatical strings was larger for the young than for the old in both experiments, Experiment 1, $t(38) = 4.17$, $p < .001$, and Experiment 2, $t(38) = 2.64$, $p = .012$.

This pattern indicates that both age groups learned the grammatical form classes of the artificial language in both tasks, with each distinguishing grammatical from ungrammatical strings and, importantly, accurately generalizing the AXB structure to the withheld grammatical novel strings. However, the interaction of String Type × Age indicates that older adults were less confident than the young in discriminating grammatical from ungrammatical strings.

It is possible that the age difference reported above reflects an age difference in response bias (e.g., a tendency to rate the strings as high) rather than a difference in learning per se. To investigate

[3] Analyses with raw rating scores showed the same pattern of results, with the critical interaction remaining significant for Experiment 1, $F(2, 72) = 10.989$, $p < .0001$, $\eta_p^2 = .23$, and Experiment 2, $F(2, 72) = 4.585$, $p = .013$, $\eta_p^2 = .11$.

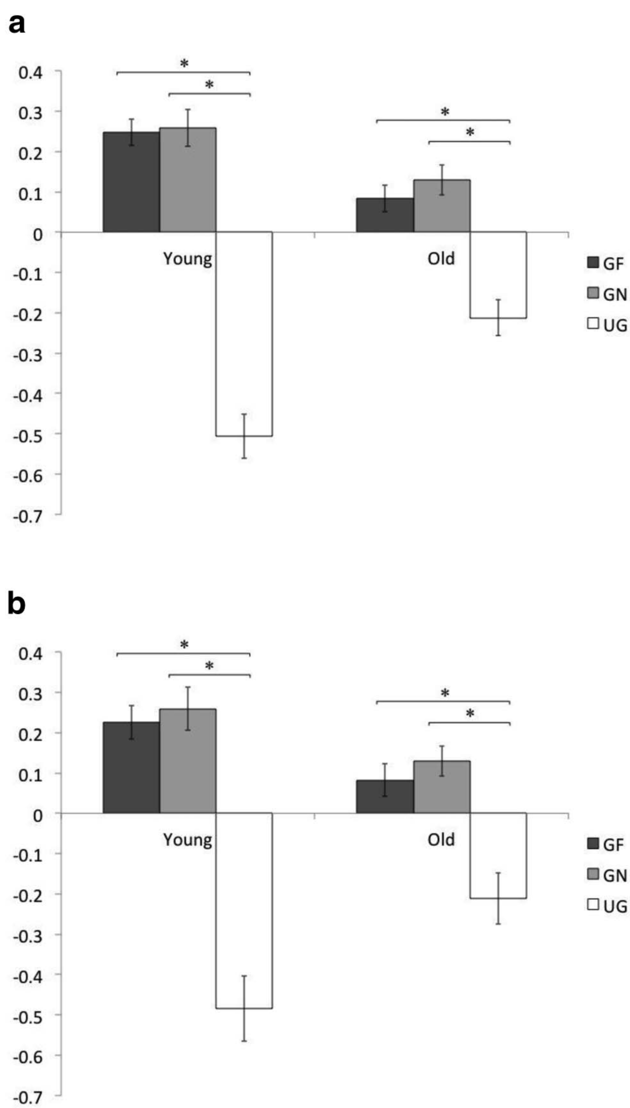

Figure 1. Average z-scored ratings for younger adults and older adults on grammatical familiar (GF), grammatical novel (GN), and ungrammatical (UG) sentence strings for Experiment 1 (a) and Experiment 2 (b). Error bars represent +/− 1 *SE*, and asterisks show significant differences ($p < .05$).

this, we carried out an additional analysis using a nonparametric theory of signal detection approach that determines separate measures of sensitivity (A) and response bias (b), with bias-free sensitivity scores ranging from 0.5 (chance) to 1.0 (perfect discrimination between grammatical and ungrammatical sentences; see Zhang & Mueller, 2005). For this analysis we defined a *hit* as rating 4 or 5 given a grammatical test string and a *false alarm* as rating 4 or 5 given an ungrammatical string. Results revealed that younger adults were significantly more sensitive than old in Experiment 1, 0.707 vs. 0.611, respectively, $t(36.99) = 3.23$, $p < .003$, and marginally more sensitive in Experiment 2, 0.693 vs. 0.620, respectively, $t(37.97) = 1.88$, $p < .068$. In contrast, the older and younger adults did not differ significantly on the measure of bias (b) in either experiment: Experiment 1, $t(35.58) = 1.12$, $p = .270$; Experiment 2: $t(32.91) = 1.17$, $p = .248$. These analyses show that the age differences reflect sensitivity, not response bias, confirming that older adults could not discriminate between grammatical and ungrammatical strings as well as young adults.

Finally, we examined the relationship between statistical learning and the demographic variables of years of education, vocabulary, and working memory. We found that the magnitude of participants' grammatical versus ungrammatical difference scores did not correlate significantly with any of these variables for either age group, making it unlikely that they are driving the observed age differences in statistical learning. (For years of education: older adults in Experiment 1: $R = -.17$, $p = .47$, and Experiment 2: $R = -.01$, $p = .97$, and younger adults in Experiment 1: $R = -.25$, $p = .29$, and Experiment 2: $R = -.18$, $p = .46$. For North American Adult Reading Test vocabulary scores: older adults in Experiment 1: $R = -.36$, $p = .12$, and Experiment 2: $R = .05$, $p = .84$, and younger adults in Experiment 1: $R = -.20$, $p = .39$, and Experiment 2: $R = .20$, $p = .83$. For Backward Digit Span working memory scores: older adults in Experiment 1: $R = -.26$, $p = .27$, and Experiment 2: $R = -.30$, $p = .21$, and younger adults in Experiment 1: $R = -.15$, $p = .52$, and Experiment 2: $R = .20$, $p = .42$.)

Discussion

Two experiments examined the extent to which older adults can acquire the grammatical form classes of an artificial language from distributional information alone. We found that after brief exposure to strings generated by an artificial grammar, young participants rated both grammatical familiar and grammatical novel strings significantly higher than ungrammatical ones, but not as different from each other. This replicates Reeder et al. (2013) and is consistent with their distributional learning hypothesis (e.g., Mintz, 2003). Further, older adults revealed this same pattern of results, making this the first study to show that older adults are also able to engage in this form of statistical learning. Nonetheless, we also found an age difference: The difference between ratings of grammatical and ungrammatical strings was smaller for old than young participants, suggesting that they had learned less than young adults.

Given that the experiments differed in their exposure conditions and test instructions, it is important that both yielded the same pattern of age effects. Unlike Reeder et al. (2013), Experiment 1 used an alien game to make the task engaging and to ensure that both age groups paid attention. Experiment 2 used the listen-only version of the task (as in Reeder et al., 2013) with the same result, indicating that the older people were not simply distracted by the complex visual stimuli in the alien game of Experiment 1. In addition, although participants in Experiment 1 made a recognition rating (i.e., whether the alien had said the sentence before), participants in Experiment 2 made a grammaticality rating (i.e., whether the sentence sounded like it came from the exposure language). Thus, the pattern of age-related similarities and differences we observed is not limited to a single set of experimental conditions.

The age difference in discrimination between grammatical and ungrammatical strings is unlikely due to an age-related working memory deficit, as performance in the task was unrelated to

Backward Digit Span scores in both age groups across experiments. This finding is consistent with previous work showing that statistical learning is unrelated to working memory (e.g., Frost, Siegelman, Narkiss & Afek, 2013; Siegelman & Frost, 2015). Nonetheless, we cannot completely rule out a contribution of working memory, because we had only one measure of it here, and, though unusual, some studies have reported a relationship (Misyak & Christiansen, 2012). Nor can we rule out the influence of potential age differences in language experience. We did ensure that all of our participants were monolingual native English speakers, but older adults are likely to have had more exposure to different languages, which could influence their ability to extract statistical regularities from linguistic input. Yet previous research found that increased bilingual experience related to more successful statistical learning in an artificial Morse code language (Bartolotti, Marian, Schroeder, & Shook, 2011). Thus, if anything, older adults' increased language experience might have helped them in our task.

What, then, are people learning in our experiments, and what does the pattern of age differences and similarities reveal about exactly how statistical learning varies with adult age? Statistical learning involves the gradual acquisition of information about the distribution of elements in input (Aslin & Newport, 2012). In the present experiments, given the composition of the exposure and test sequences, bigram frequency (e.g., of AX, XB words) is the simplest kind of information that would enable people to discriminate grammatical from ungrammatical test strings, while not discriminating grammatical novel from grammatical familiar strings. Had participants only learned the frequencies of individual words in the exposure set, they would have been unable to discriminate grammatical from ungrammatical test strings, because word frequency was the same for both—and yet they did. Furthermore, had they been learning specific sequences of three or more words (e.g., $A_1X_1B_1$), they would have discriminated Grammatical Novel from Grammatical Familiar strings—and yet they did not. But bigram frequency, as well as a number of other more complex statistical computations based on word combinations, would allow learners to succeed at precisely the discriminations shown by both age groups.

To identify what young people were learning, Reeder et al. (2013) varied characteristics of the exposure set across a series of experiments. Because ours was the first to examine such grammatical form class learning in older adults, we simplified our studies by using only one of their possible exposure sets, one characterized by complete overlap, such that each X word appeared in the presence of every A and every B word, and by sparse density, in that the exposure set contained only nine of the 27 possible grammatical sentences (Reeder et al.'s Experiment 2). Comparing across their experiments, Reeder et al. found that reducing the amount of overlap resulted in young people distinguishing between grammatical novel and grammatical familiar strings, suggesting that overlap affected degree of generalization. In contrast, increasing density and overall exposure (the latter by increasing the number of presentations of the exposure set) resulted in an increase in the size of the grammatical versus ungrammatical difference, suggesting that density and/or overall exposure increased the amount of detail learned about the exposure set.

It was this latter difference—in the size of the grammatical versus ungrammatical difference—that was smaller for our older than our young participants. This effect suggests that our older adults had built up a less detailed representation of the exposure set. This idea is consistent with evidence from the memory literature that older adults engage in more gist-based processing than young, which is related to their reduced item specific processing at exposure, reduced differentiation in processing targets versus lures at retrieval (e.g., see Dennis, Bowman, & Peterson, 2014 for review), and, most recently, to reduced differentiation in recruitment of learning- and memory-related brain networks (e.g., Bowman & Dennis, 2015). In a related vein, Campbell, Hasher, and Thomas (2010) have suggested that older adults may actually bind too much information, which results in them forming overly broad associations between nearby events in their environment. Thus, older adults may have formed associations not only between items within individual sentence strings, but also across the entirety of the language input, making it more difficult for them to distinguish grammatical and ungrammatical strings.

The present study has established that older adults can learn grammatical form classes, but additional work is needed to determine whether the age differences we found reflect quantitative or qualitative differences. For example, to isolate what is being learned and what improves learning for each age group, future studies should vary characteristics of the exposure set and test items, to identify whether both ages are influenced in the same way. Additional work could also investigate whether older adults' difficulties with speech perception contribute to the age difference in learning. We did not perform auditory screening here, and so it is possible that the older adults were not able to hear the input as well (e.g., Seifert, Hoffnung, & Hoffnung, 2000). However, the fact that they gave higher ratings to grammatical than ungrammatical strings suggests that they were able to hear differences among the strings. Even so, the additional effort they might have had to expend to identify the words could have reduced the resources available for encoding and learning (Wingfield, Tun, & McCoy, 2005; Roberts & Allen, 2016).

Our findings are consistent with growing evidence that some implicit forms of learning, particularly those involving the acquisition of subtle probabilistic sequential regularities, show age-related declines (e.g., Janacsek, Fiser, & Nemeth, 2012; Lukács & Kemény, 2015; Stillman, Howard, & Howard, 2016; Weiermann & Meier, 2012; see Howard & Howard, 2012, 2013 and Rieckmann & Bäckman, 2009 for reviews). Researchers have argued that statistical learning and implicit sequence learning reflect the same domain-general cognitive process (Hunt & Aslin, 2010; Perruchet & Pacton, 2006; Turk-Browne, 2012), and there is evidence for similar neural substrates as well (Karuza et al., 2013; Simon, Vaidya, Howard, & Howard, 2012). Our findings reveal another similarity between implicit and statistical learning: reduced learning in older adults. Although the procedure used here, as in many statistical learning studies, is different from implicit learning tasks—in that participants were told that there would be a subsequent memory test—other statistical learning studies have shown that children and young adults learn about the structure of an artificial language even from incidental exposure alone and that the density of patterned linguistic information in such studies typically produces implicit rather than explicit learning, regardless of instructions (Saffran, Newport, Aslin, Tunick, & Barrueco, 1997). Future studies should further test the similarity in age-related differences between these two types of learning tasks. For example, the magnitude of age differences in implicit probabilistic sequence learning tasks has been shown to increase with extended practice (Howard et al., 2004; Stillman, Howard, & Howard, 2016), with young adults continuing to learn to higher levels, even as older adults reach asymptote. Whether this pattern would also occur for the present form of statistical learning, or would instead show reduced age differences with more exposure, is unknown.

Finally, our findings may also have implications for second language (L2) learning in late adulthood. Research on language learning over development has largely focused on learning during childhood versus young adulthood (and whether there is a critical or sensitive period for language learning; see Johnson & Newport, 1989; Birdsong & Molis, 2001; Newport, 2016); very little research has been done on whether L2 learning undergoes additional changes during aging in later life. Several laboratory studies have indicated that older learners (over age 65) are poorer at L2 learning than younger adults (Mackey & Sachs, 2012; van der Hoeven & de Bot, 2012), but this is not always the case (Lenet, Sanz, Lado, Howard, & Howard, 2011). These studies have attributed such differences to age differences in working memory (e.g., Mackey & Sachs, 2012) or in declarative associative memory (e.g., van der Hoeven & de Bot, 2012). Our findings suggest that changes in statistical learning during aging might be another potential source of L2 learning differences.

In summary, we have shown that older adults are capable of statistical learning of the distributional information underlying grammatical form class categories, following brief auditory exposure to a subset of possible strings of the language. However, they are poorer than young adults at discriminating grammatical from ungrammatical strings, suggesting they learn less detail about the exposure set. Future research on the aging of statistical learning will not only broaden our understanding of age differences in implicit forms of learning, but will also help to identify what is being learned, how this differs with adult age, and the conditions under which such learning can be enhanced.

References

Aslin, R. N., & Newport, E. L. (2012). Statistical learning: From acquiring specific items to forming general rules. *Current Directions in Psychological Science, 21,* 170–176. http://dx.doi.org/10.1177/0963721412436806

Aslin, R. N., & Newport, E. L. (2014). Distributional language learning: Mechanisms and models of category formation. *Language Learning, 64* (Suppl. 2), 86–105.

Bartolotti, J., Marian, V., Schroeder, S. R., & Shook, A. (2011). Bilingualism and inhibitory control influence statistical learning of novel word forms. *Frontiers in Psychology, 2,* 324. http://dx.doi.org/10.3389/fpsyg.2011.00324

Birdsong, D., & Molis, M. (2001). On the evidence for maturational constraints in second-language acquisition. *Journal of Memory and Language, 44,* 235–249. http://dx.doi.org/10.1006/jmla.2000.2750

Bowman, C. R., & Dennis, N. A. (2015). Age differences in the neural correlates of novelty processing: The effects of item-relatedness. *Brain Research, 1612,* 2–15. http://dx.doi.org/10.1016/j.brainres.2014.08.006

Campbell, K. L., Hasher, L., & Thomas, R. C. (2010). Hyper-binding: A unique age effect. *Psychological Science, 21,* 399–405. http://dx.doi.org/10.1177/0956797609359910

Campbell, K. L., Zimerman, S., Healey, M. K., Lee, M. M., & Hasher, L. (2012). Age differences in visual statistical learning. *Psychology and Aging, 27,* 650–656. http://dx.doi.org/10.1037/a0026780

Cartwright, T. A., & Brent, M. R. (1997). Syntactic categorization in early language acquisition: Formalizing the role of distributional analysis. *Cognition, 63,* 121–170. http://dx.doi.org/10.1016/S0010-0277(96)00793-7

Dennis, N. A., Bowman, C. R., & Peterson, K. M. (2014). Age-related differences in the neural correlates mediating false recollection. *Neurobiology of Aging, 35,* 395–407. http://dx.doi.org/10.1016/j.neurobiolaging.2013.08.019

Ettlinger, M., Morgan-Short, K., Faretta-Stutenberg, M., & Wong, P. C. (2015). The relationship between artificial and second language learning. *Cognitive Science, 40,* 822–847. http://dx.doi.org/10.1111/cogs.12257

Fiser, J., & Aslin, R. N. (2001). Unsupervised statistical learning of higher-order spatial structures from visual scenes. *Psychological Science, 12,* 499–504. http://dx.doi.org/10.1111/1467-9280.00392

Folstein, M. F., Folstein, S. E., & McHugh, P. R. (1975). "Mini-mental state". A practical method for grading the cognitive state of patients for the clinician. *Journal of Psychiatric Research, 12,* 189–198. http://dx.doi.org/10.1016/0022-3956(75)90026-6

Frost, R., Siegelman, N., Narkiss, A., & Afek, L. (2013). What predicts successful literacy acquisition in a second language? *Psychological Science, 24,* 1243–1252. http://dx.doi.org/10.1177/0956797612472207

Howard, D. V., & Howard, J. H., Jr. (2012). Dissociable forms of implicit learning in aging. In M. Naveh-Benjamin & N. Ohta (Eds.), *Perspectives on human memory and aging* (pp. 121–151). New York, NY: Psychology Press.

Howard, D. V., Howard, J. H., Jr., Japikse, K., DiYanni, C., Thompson, A., & Somberg, R. (2004). Implicit sequence learning: Effects of level of structure, adult age, and extended practice. *Psychology and Aging, 19,* 79–92. http://dx.doi.org/10.1037/0882-7974.19.1.79

Howard, J. H., Jr., & Howard, D. V. (2013). Aging mind and brain: Is implicit learning spared in healthy aging? *Frontiers in Psychology, 4,* 817. http://dx.doi.org/10.3389/fpsyg.2013.00817

Hunt, R. H., & Aslin, R. N. (2010). Category induction via distributional analysis: Evidence from a serial reaction time task. *Journal of Memory and Language, 62,* 98–112. http://dx.doi.org/10.1016/j.jml.2009.10.002

Janacsek, K., Fiser, J., & Nemeth, D. (2012). The best time to acquire new skills: Age-related differences in implicit sequence learning across the human lifespan. *Developmental Science, 15,* 496–505. http://dx.doi.org/10.1111/j.1467-7687.2012.01150.x

Johnson, J. S., & Newport, E. L. (1989). Critical period effects in second language learning: The influence of maturational state on the acquisition of English as a second language. *Cognitive Psychology, 21,* 60–99. http://dx.doi.org/10.1016/0010-0285(89)90003-0

Karuza, E. A., Newport, E. L., Aslin, R. N., Starling, S. J., Tivarus, M. E., & Bavelier, D. (2013). The neural correlates of statistical learning in a word segmentation task: An fMRI study. *Brain and Language, 127,* 46–54. http://dx.doi.org/10.1016/j.bandl.2012.11.007

Lenet, A. E., Sanz, C., Lado, B., Howard, J. H., Jr., & Howard, D. V. (2011). Aging, pedagogical conditions, and differential success in SLA: An empirical study. In C. Sanz & R. P. Leow (Eds.), *Implicit and explicit language learning: Conditions, processes, and knowledge in SLA and bilingualism* (pp. 73–84). Washington, DC: Georgetown University Press.

Lukács, Á., & Kemény, F. (2015). Development of different forms of skill learning throughout the lifespan. *Cognitive Science, 39,* 383–404. http://dx.doi.org/10.1111/cogs.12143

Mackey, A., & Sachs, R. (2012). Older learners in SLA research: A first look at working memory, feedback, and L2 development. *Language Learning, 62,* 704–740. http://dx.doi.org/10.1111/j.1467-9922.2011.00649.x

Midford, R., & Kirsner, K. (2005). Implicit and explicit learning in aged and young adults. *Aging, Neuropsychology and Cognition, 12,* 359–387. http://dx.doi.org/10.1080/13825580500246894

Mintz, T. H. (2002). Category induction from distributional cues in an artificial language. *Memory & Cognition, 30,* 678–686. http://dx.doi.org/10.3758/BF03196424

Mintz, T. H. (2003). Frequent frames as a cue for grammatical categories in child directed speech. *Cognition, 90,* 91–117. http://dx.doi.org/10.1016/S0010-0277(03)00140-9

Mintz, T. H., Newport, E. L., & Bever, T. G. (1995). Distributional regularities of form class in speech to young children. In J. N. Beckman (Ed.), *Proceedings of NELS 25* (vol. 2, pp. 43–54). Amherst, MA: Graduate Linguistic Student Association.

Mintz, T. H., Newport, E. L., & Bever, T. G. (2002). The distributional structure of grammatical categories in speech to young children. *Cognitive Science, 26,* 393–424. http://dx.doi.org/10.1207/s15516709cog2604_1

Misyak, J. B., & Christiansen, M. H. (2012). Statistical learning and language: An individual differences study. *Language Learning, 62,* 302–331. http://dx.doi.org/10.1111/j.1467-9922.2010.00626.x

Neger, T. M., Rietveld, T., & Janse, E. (2014). Relationship between perceptual learning in speech and statistical learning in younger and older adults. *Frontiers in Human Neuroscience, 8,* 628. http://dx.doi.org/10.3389/fnhum.2014.00628

Newport, E. L. (2016). (in press). Statistical language learning: Computational, maturational and linguistic constraints. *Language and Cognition*.

Perruchet, P., & Pacton, S. (2006). Implicit learning and statistical learning: One phenomenon, two approaches. *Trends in Cognitive Sciences, 10,* 233–238. http://dx.doi.org/10.1016/j.tics.2006.03.006

Reber, A. S. (1967). Implicit learning of artificial grammars. *Journal of Verbal Learning & Verbal Behavior, 6,* 855–863. http://dx.doi.org/10.1016/S0022-5371(67)80149-X

Reeder, P. A., Newport, E. L., & Aslin, R. N. (2013). From shared contexts to syntactic categories: The role of distributional information in learning linguistic form-classes. *Cognitive Psychology, 66,* 30–54. http://dx.doi.org/10.1016/j.cogpsych.2012.09.001

Rieckmann, A., & Bäckman, L. (2009). Implicit learning in aging: Extant patterns and new directions. *Neuropsychology Review, 19,* 490–503. http://dx.doi.org/10.1007/s11065-009-9117-y

Roberts, K. L., & Allen, H. A. (2016). Perception and cognition in the ageing brain: A brief review of the short-and long-term links between perceptual and cognitive decline. *Frontiers in Aging Neuroscience, 8,* 39.

Saffran, J. R. (2002). Constraints on statistical language learning. *Journal of Memory and Language, 47,* 172–196. http://dx.doi.org/10.1006/jmla.2001.2839

Saffran, J. R., Aslin, R. N., & Newport, E. L. (1996). Statistical learning by 8-month-old infants. *Science, 274,* 1926–1928. http://dx.doi.org/10.1126/science.274.5294.1926

Saffran, J. R., Newport, E. L., Aslin, R. N., Tunick, R. A., & Barrueco, S. (1997). Incidental language learning: Listening (and learning) out of the corner of your ear. *Psychological Science, 8,* 101–105. http://dx.doi.org/10.1111/j.1467-9280.1997.tb00690.x

Seifert, K., Hoffnung, R. J., & Hoffnung, M. (2000). *Lifespan development*. Boston, MA: Houghton Mifflin Company.

Siegelman, N., & Frost, R. (2015). Statistical learning as an individual ability: Theoretical perspectives and empirical evidence. *Journal of Memory and Language, 81,* 105–120. http://dx.doi.org/10.1016/j.jml.2015.02.001

Simon, J. R., Vaidya, C. J., Howard, J. H., Jr., & Howard, D. V. (2012). The effects of aging on the neural basis of implicit associative learning in a probabilistic triplets learning task. *Journal of Cognitive Neuroscience, 24,* 451–463. http://dx.doi.org/10.1162/jocn_a_00116

Stillman, C. M., Howard, J. H., Jr., & Howard, D. V. (2016). The effects of structural complexity on age-related deficits in implicit probabilistic sequence learning. *The Journals of Gerontology Series B, Psychological Sciences and Social Sciences, 71,* 212–219. http://dx.doi.org/10.1093/geronb/gbu135

Turk-Browne, N. B. (2012). Statistical learning and its consequences. In M. D. Dodd & J. H. Flowers (Eds.), *The influence of attention, learning, and motivation on visual search* (pp. 117–146). New York, NY: Springer. http://dx.doi.org/10.1007/978-1-4614-4794-8_6

Turk-Browne, N. B., Scholl, B. J., Chun, M. M., & Johnson, M. K. (2009). Neural evidence of statistical learning: Efficient detection of visual regularities without awareness. *Journal of Cognitive Neuroscience, 21,* 1934–1945. http://dx.doi.org/10.1162/jocn.2009.21131

Uttl, B. (2002). North American Adult Reading Test: Age norms, reliability, and validity. *Journal of Clinical and Experimental Neuropsychology, 24,* 1123–1137. http://dx.doi.org/10.1076/jcen.24.8.1123.8375

van der Hoeven, N., & de Bot, K. (2012). Relearning in the elderly: Age-related effects on the size of savings. *Language Learning, 62,* 42–67. http://dx.doi.org/10.1111/j.1467-9922.2011.00689.x

Wechsler, D. (1997). *WAIS–III administration and scoring manual* (3rd ed.). San Antonio, TX: Psychological Corporation.

Weiermann, B., & Meier, B. (2012). Incidental sequence learning across the lifespan. *Cognition, 123,* 380–391. http://dx.doi.org/10.1016/j.cognition.2012.02.010

Wingfield, A., Tun, P. A., & McCoy, S. L. (2005). Hearing loss in older adulthood: What it is and how it interacts with cognitive performance. *Current Directions in Psychological Science, 14,* 144–148. http://dx.doi.org/10.1111/j.0963-7214.2005.00356.x

Zhang, J., & Mueller, S. T. (2005). A note on ROC analysis and non-parametric estimate of sensitivity. *Psychometrika, 70,* 203–212. http://dx.doi.org/10.1007/s11336-003-1119-8

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