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Executive function predicts artificial language learning

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Abstract

Previous research suggests executive function (EF) advantages among bilinguals compared to monolingual peers, and these advantages are generally attributed to experience controlling two linguistic systems. However, the possibility that the relationship between bilingualism and EF might be bidirectional has not been widely considered; while experience with two languages might improve EF, better EF skills might also facilitate language learning. In the current studies, we tested whether adults' and preschool children's EF abilities predicted success in learning a novel artificial language. After controlling for working memory and English receptive vocabulary, adults' artificial language performance was predicted by their inhibitory control ability (Study 1) and children's performance was predicted by their attentional monitoring and shifting ability (Study 2). These findings provide preliminary evidence suggesting that EF processes may be employed during initial stages of language learning, particularly vocabulary acquisition, and support the possibility of a bidirectional relationship between EF and language acquisition.

Keywords

executive function; artificial language; inhibition; attentional monitoring; attentional shifting; working memory

Introduction

Acquiring and speaking two languages places additional cognitive control demands on multilingual speakers compared to individuals who speak a single language. Evidence from previous research suggests that non-linguistic cognitive control skills are advantaged in bilingual individuals when compared to their monolingual peers. Cognitive advantages of bilingualism have been widely reported among children (Bialystok, 1999; Bialystok & Martin, 2004; Carlson & Meltzoff, 2008; Yoshida, Tran, Benitez, & Kuwabara, 2011) and adults (Bialystok, Craik, & Freedman, 2007; Bialystok, Craik, Klein, & Viswanathan, 2004;

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Bialystok, Craik, & Luk, 2008; Costa, Hernández, Costa-Faidell, & Sebastià-Gallès, 2009; Costa, Hernández, Sebastià-Gallès, 2008; Prior & MacWhinney, 2010) who are proficient in two language systems. Among the specific skills reportedly advantaged among bilinguals are inhibitory control (Carlson & Meltzoff, 2008), cognitive flexibility (Ibrahim, Shoshani, Prior, & Share, 2013), attentional shifting (Prior & MacWhinney, 2010) and attentional monitoring (Costa et al., 2009; Kapa & Colombo, 2013). Such higher-order cognitive skills that control attention, thought, and behavior are collectively referred to as *executive function* (EF).

Miyake, Friedman, Emerson, Witzki, and Howerter (2000) identified three components of EF that are related but separable. Inhibitory control reflects one's ability to deliberately inhibit or prevent prepotent/automatic responses. Shifting is the ability to switch attention between tasks, operations, or stimulus properties. Attentional monitoring, which is part of the process of *updating* (Miyake et al., 2000), captures the ability to monitor the environment for changes in stimuli/task demands and alter responding accordingly. Although these EF skills are also necessary for monolingual language use (Paap & Greenberg, 2013), the additional cognitive demands of bilingualism are assumed to result in greater use of these skills, which in turn leads to bilingual advantages even on non-linguistic tasks (Green, 1998). Previous studies have reported bilingual advantages for each of these EF components.

Researchers hypothesize that the EF advantages of bilingualism are the result of bilinguals continually practicing domain-general EF processes while controlling two language systems. For example, during lexical access, bilinguals must maintain separation between their two languages (see Bialystok & Craik, 2010 for review) in order to correctly access the target language and avoid accessing the non-target language. Both behavioral (Marian & Spivey, 2003a; 2003b; Poulisse, 2000; Schwartz & Kroll, 2006) and neuroimaging evidence (Abutalebi et al., 2007; Christoffels, Firk, & Schiller, 2007; Hoshino & Thierry, 2011; Jeong et al., 2007; Marian, Spivey, & Hirsch, 2003; Misra, Guo, Bobb, & Kroll, 2012; van Heuven, Schriefers, Dijkstra, & Hagoort, 2008) suggests that when speaking or listening to one of their languages, bilinguals' other languages are simultaneously activated. Therefore, bilinguals may use cognitive control processes to maintain control over their two languages. Bilinguals likely employ domain-general inhibitory control (Green, 1998; Kroll, Bobb, Misra, & Guo, 2008; Meuter, 2005) to prevent lexical access in the non-target language, which in turn leads to improvements in these control mechanisms even when tested using nonlinguistic measures.

Additionally, bilinguals may use attentional monitoring to determine which of their languages they should use based on the language used by their interlocutors (Costa et al., 2009; Crinion et al., 2006; Soveri, Rodriguez-Fornells, & Laine, 2011). Finally, bilinguals may rely on attentional shifting when it is necessary to switch between their two languages (Abutalebi & Green, 2008; Costa & Santesteban, 2004; Jackson, Swainson, Cunningham, & Jackson, 2001; Hernandez, Dapretto, Mazziotta, & Bookheimer, 2001; Meuter & Allport, 1999; Prior & Gollan, 2011; Thomas & Allport, 2000) due to either code switching or changing between communication partners.

It should be noted, however, that other research does not support a bilingual advantage in non-linguistic control processes (see Hilchey & Klein, 2011 for review). For example, Paap and Greenberg (2013) found no differences in performance between bilinguals and monolinguals on three measures of inhibitory control – an antisaccade task, a Simon task, and a flanker task – nor was there a bilingual advantage on an attentional switching task. Likewise, Kousaie and Phillips (2012) reported no bilingual advantage on a battery of inhibitory control tasks, and Hernández, Martin, Barceló, and Costa (2013) found that bilinguals and monolinguals performed equally on switching tasks. Duñabeitia et al. (2013) also reported that a comparison between a large sample of bilingual and monolingual children revealed equal inhibition abilities between these two groups. Thus, although frequently reported, bilingual advantages in non-linguistic cognitive control are not without well-documented exceptions.

When bilingual cognitive advantages are found, it is typically assumed that bilingual experience leads to better EF performance. However, little attention has been paid to the reverse causal possibility. It is theoretically possible that the additional cognitive demands of bilingualism may be less challenging to individuals who are already equipped with strong EF skills. For example, an individual may be more successful at learning to produce a novel label for an object if she can use inhibitory control to suppress the prepotent response of labeling the object in her native language. Therefore, individual differences in EF abilities may affect how easily an L2 can be acquired and controlled. In other words, individuals with better EF abilities may be more likely to become proficient, balanced bilinguals.

Evidence of the role of EF in language control comes from research comparing the language control abilities of bilinguals who differ in levels of EF. Indeed, among bilinguals, individuals with better EF abilities demonstrate less difficulty controlling their two languages. Festman, Rodriguez-Fonells, & Munte (2010) reported that bilingual adults who were better able to avoid interference from their non-target language during a bilingual picture naming task (*non-switchers*) outperformed *switchers* (i.e., those participants who made more non-target language errors) on a battery of non-linguistic EF tasks. Additional evidence of the role of EF in L2 production comes from neuroimaging research. Hernandez and Meschyan (2006) reported that when covertly naming pictures in their weaker L2, there was a significant activation increase in participants' dorsolateral prefrontal cortex and anterior cingulate gyrus, which are brain regions that have been shown to be significantly activated during task-switching and inhibition tasks. These fMRI findings led Hernandez and Meschyan (2006) to conclude that bilingual participants were likely engaging in similar EF processes while producing their non-dominant L2.

Furthermore, the possibility that individual differences in EF abilities are related to language control abilities is consistent with studies of monolingual participants suggesting that individuals with better cognitive control are more successful at processing ambiguous sentences (see Novick, Trueswell, & Thompson-Schill, 2005, for review). For example, in a recent study, Novick, Hussey, Teubner-Rhodes, Harbison, and Bunting (2014) found that improvements in non-linguistic cognitive control abilities, specifically conflict-resolution, through a training program also led to improved ability to avoid misinterpretation of ambiguous garden-path sentences.

A similar relationship exists between EF ability and L2 learning. Linck, Kroll, and Sunderman (2009) examined individuals' access to their L1 after 3 months of an L2 immersion experience. These adult learners were found to have reduced access to their L1 as evidenced by a decreased interference effect of L1 translation distractors in a judgment task that required participants to rate whether a pair of L1 and L2 words were translation equivalents. Additionally, L2 immersion experience resulted in reduced performance on an L1 fluency task. These findings led Linck et al. (2009) to conclude that L2 learners were inhibiting access to their L1 in order to successfully acquire an L2, which led to a reduction in access to the L1 during judgment and fluency tasks.

Additional evidence of the role of EF in L2 learning comes from an fMRI study in which researchers compared neural activation when participants were switching between their L1 (Chinese) and the L2 they were learning at the time of testing (English; Wang, Xue, Chen, Xue, & Dong, 2007). Participants had begun learning their L2 after the age of 12 and were considered to have low to intermediate L2 proficiency. When learners switched from their L1 to their L2, Wang et al. (2007) observed increased activation in areas associated with EF processing, including bilateral frontal cortices and the left anterior cingulate cortex, which resulted in the conclusion that even among L2 learners, L1 inhibition is necessary during L2 production.

Previous research has established the role of non-linguistic EF skills in language processing among bilingual, monolingual, and L2-learner participants, which introduces the possibility that individuals with better EF skills would have advantages in language processing. In other words, individual differences in EF abilities are associated with differences in language processing abilities (Festman et al., 2010; Mercier, Pivneva, & Titone, 2014; Pivneva, Palmer, & Titone, 2012). Advancing beyond this prior research, the goal of the present study was to examine whether individuals' EF skills predict their language learning abilities.

An artificial language system was used to simulate the earliest stages of L2 learning within a controlled laboratory setting. Although many researchers consider the acquisition of artificial languages to be analogous with first language acquisition, McLaughlin (1980) argued that artificial language learning is better conceptualized as a proxy for L2 acquisition because children and adults come to the task of learning an artificial language after having already acquired a first language. Despite the utility of using artificial languages to simulate the process of natural language learning, there are certainly differences between these two processes including the relative smaller size and complexity of an artificial language compared to natural languages and the potentially unnatural methods used for teaching/exposing participants to artificial languages (Ingram & Pye, 1993). However, neuroimaging evidence suggests that participants trained on artificial/miniature languages display the same neural responses during processing as those elicited while individuals process natural languages (Forkstam, Hagoort, Fernandez, Ingvar, & Petersson, 2006; Friederici, Steinhaur, & Pfeifer, 2002; Petersson, Forkstam, & Ingvar, 2004), suggesting that there is some degree of similarity between artificial and natural language processing.

While not intended to address specific issues of *how* EF processes are used in the acquisition of a new language, the current study focused on the more basic question of whether or not

individual differences in EF may contribute to artificial language learning outcomes. This question was addressed in Study 1 by assessing monolingual adults' EF abilities and their ability to acquire receptive and productive knowledge of a novel artificial language system. In Study 2, the same method was used to assess the role of EF in artificial language learning among monolingual preschool-age children. Because our artificial language training protocol included both explicit teaching and implicit learning, the process may be considered most similar to classroom-based L2 learning.

Based on the assumption that individuals with better EF skills will be advantaged in language learning, we hypothesized that EF performance would significantly predict artificial language-learning outcomes such that individuals with better EF scores would also have higher scores on tests of artificial language learning outcomes. Verbal ability (L1) and working memory were also expected to positively predict outcomes on artificial language learning. This hypothesis is consistent with previous research linking L2 learning outcomes with L1 ability (Sparks, Patton, & Ganschow, 2012) and adults' ability to learn novel lexical items with their working memory capacity (Atkins & Baddeley, 1998; Martin & Ellis, 2012).

Participants' EF abilities were expected to account for a significant amount of variance in artificial language-learning outcomes after controlling for the effects of English verbal ability and working memory. The EF tasks used in this study assessed multiple aspects or components of EF (Miyake et al., 2000) including inhibitory control, shifting, and attentional monitoring. We did not make specific predictions regarding which of these components would be predictive of artificial language learning. However, each of these EF components have been previously identified as advantaged among bilinguals (e.g., Carlson & Meltzoff, 2008; Costa et al., 2009; Prior & MacWhinney, 2010), and therefore, it is plausible for all of them to be involved in the process of acquiring a new language.

STUDY 1

Method

Participants—The participant group comprised 87 undergraduate students enrolled in introductory psychology courses. Eight were excluded from analyses due to being non-native English speakers ($n = 1$) or failure to complete the second study session ($n = 7$). The remaining 79 participants (42 female) self-reported speaking a single language (English) fluently at the time of testing and their mean age was 19.5 years. Participants' duration and type of previous L2 exposure (along with their self-rated proficiency) was collected in a questionnaire. All participants reported having normal or corrected-to-normal vision and hearing at testing.

Artificial Language—The artificial language employed in this study was a modified version of the language created by Hudson Kam and Newport (2005). Four additional nouns were added to the artificial language based on the work of Wonnacott, Newport, and Tanenhaus (2008). Additionally, the determiner used by Hudson Kam and Newport (2005) was eliminated from the artificial language for the purposes of this study, and only four verbs were used. The resulting simplified artificial language system consisted of 12 nouns and 4 verbs. The 12 nouns were animate, real-world objects (animals or humans) and could

be both an agent (i.e., actor) and a theme (i.e., recipient of action) within the language's argument structure. Each of the four verbs described the motion of an agent (noun 1) in relation to the stationary theme (noun 2). The combination of nouns and verbs resulted in 528 possible sentences in the artificial language. The word order of the artificial language was verb-noun1-noun2.

This artificial language was very simplified compared to natural languages, as it lacked syntax (aside from linear word order), prosody, and morphology and used English phonology. Within the artificial language, agents and themes were only differentiated through word order. A complete list of the lexical items and their meanings in the artificial language are included in the appendix. The following are example sentences in the language along with glosses of their meanings.

1. */blɪt ns;rk fumpogΛ/*
 move under frog bird
 “The frog moves under the bird”
2. */flɪm fumpogΛ nsrk/*
 move around bird frog
 “The bird moves around the frog”

A highly simplified language was used in order to facilitate comparisons between adult learners in Study 1 and preschool-age (4- to 5-year-olds) child participants in Study 2. The more complex version of the language which contained a determiner was successfully used by Hudson Kam and Newport (2005) with adults and older, 5- to 7-year-old children. Our Study 2 participants were younger; we therefore reduced the demands of the language to improve their language-learning outcomes. Additionally, the participants in our studies received less total exposure to the artificial language than participants in Hudson Kam and Newport's (2005) study. As a result of this simplification, the process of acquiring the artificial language in the current studies may be primarily a task of vocabulary learning.

Materials—Participants were exposed to the artificial language via a picture book and a series of training videos that were created for the study. The book, which was used to train participants on the artificial language nouns, contained 12 images representing the 12 nouns in the artificial language with one image on each page. All of the images used in the study were acquired from Microsoft ClipArt. Using the same images, 300 animated video segments were created, which each presented a unique verb-noun 1-noun 2 combination in the artificial language. For example, an animation might demonstrate a frog jumping on top of a rhinoceros while simultaneously playing the audio ‘*Luks nsrk nagrΛ*.’ Each video segment was six seconds in length and a single female speaker produced the narrations with equal stress on each word, and within the video training each verb and noun were presented an equal number of times (i.e., 75 presentations of each verb and 50 presentations of each noun).

Measures

Peabody Picture Vocabulary Test – 4: English receptive vocabulary was measured using the Peabody Picture Vocabulary Test—Fourth Edition (PPVT-4; Dunn & Dunn, 2007), which is a standardized picture-selection measure of receptive vocabulary.

Digit span: Working memory was measured using forward and backward digit span tasks (for limitations of this measure as compared to complex span tasks of working memory see Engle, Tuholski, Laughlin, & Conway, 1999). In the forward digit span task, the experimenter read increasingly long lists of numbers to participants who repeated the list in the same order. The backward digit span was identical to the forward digit span task except participants repeated the list of numbers in reverse order. In both span tasks list length began at two digits and increased by one digit until participants made errors on two lists of a given span. Participants were awarded one point for each correctly repeated list and a score of zero for each incorrect repetition. Scores from the backward and forward digit span tasks were summed to create a single digit span score for analyses. Working memory is often considered a component of EF (Miyake et al., 2000). Although most researchers do not report working memory advantages among bilingual individuals (e.g., Bialystok, Craik, & Luk, 2008), extant research suggests that working memory is involved in language learning (Atkins & Baddeley, 1998). Therefore, participants' working memory ability was measured in order to control for the effect of working memory on artificial language outcomes and isolate the effects of those EF skills that are reportedly advantaged among bilinguals (e.g., inhibitory control, attentional monitoring, shifting).

Visual Simon task: The visual Simon task is a computerized EF measure in which participants viewed colored target squares presented on a computer screen and used a key-press to respond to the color of the visual target. The task was administered via INQUISIT 4.0.0 (Millisecond Software, 2012) software for the first 45 participants tested and via E-Prime 2.0 (Schneider, Eschmann, & Zuccoloto, 2002) for the remaining 34 participants.¹ The task required participants to press a key located to the left of the computer keyboard in response to blue targets and a key on the right side of the keyboard in response to red targets. Visual targets were presented either on the left or right sides of the screen, resulting in congruent trials (i.e., target key spatially aligned with the visual target) or incongruent trials (i.e., target key opposite from visual target).

The specific version of the visual Simon task employed in the current study was based on the task used by Bialystok et al. (2004) in terms of stimulus timing, training criteria, and number of trials. Targets remained on the screen for 1000ms or until participants made a

¹Participants who completed version of the visual Simon task administered via INQUISIT versus E-Prime software performed equally on overall reaction time, $t(77) = .40$, $p = .69$, and accuracy, $t(77) = -1.1$, $p = .29$. However, the groups differed significantly in their Simon effect scores, with participants completing the task in INQUISIT having significantly larger mean Simon effect scores (29.3) compared to participants who completed the E-Prime version (-58), $t(77) = -3.76$, $p < .001$. This group difference is likely the result of variation in participants across sampling time (i.e., early participants tested during the fall academic semester completed the INQUISIT version while later participants tested during the spring academic semester completed the E-prime version) because the same difference was found on a similar measure of inhibitory control, ANT executive network score, which was administered identically across all participants via E-Prime. Specifically, participants who completed the INQUISIT version of the visual Simon task had significantly higher average ANT executive network scores (115.8) than participants who completed the E-Prime Simon task (97.5), $t(77) = -2.13$, $p = .04$. Despite the differences between these groups, inclusion of visual Simon task version (i.e., INQUISIT versus E-Prime) as a covariate in analyses does not change reported outcomes.

response. Participants began the task by completing practice trials, which continued until they made eight consecutive correct responses. Following practice, participants completed a test phase of 28 trials, with 14 congruent and 14 incongruent trials presented in a randomized order. A Simon effect score was calculated for each participant by subtracting their average response time to congruent trials from response time to incongruent trials, with a smaller Simon effect score indexing better inhibitory control (Bialystok et al., 2004). Participants' reaction time averaged across both congruent and incongruent trials served as a measure of attentional monitoring. Faster average reaction time has been previously interpreted as indicating better attentional monitoring, or less disruption from the need to switch between the randomly intermixed congruent and incongruent trial types within the task (Costa et al. 2009). Only trials with correct responses were included in calculating these outcome scores.

Attention Network Test: The Attention Network Test (Fan, McCandliss, Sommer, Raz, & Posner, 2003) is a computerized flanker task, which includes varied cues presented before each flanker trial. The task was administered using E-Prime 2.0 software (Schneider et al., 2002). Participants used a mouse button press to respond to the directional orientation (i.e., left or right) of a central target arrow. The target arrow was presented in one of three flanker trial types: neutral trials included a target arrow without flanker arrows (----→----), congruent trials included two arrows flanking the target oriented in the same direction (→→→→→→), incongruent trials included a target arrow flanked by two arrows oriented in the opposite direction (←←←→←←). Each target remained on the screen until the participant provided a response or until 1700ms elapsed. Participants began the task by completing 24 practice trials during which they received feedback from the program regarding their accuracy and response speed and then completed two test blocks each containing 96 trials (192 total). The standard version of the task (Fan et al. 2003) includes three trial blocks of 96 test trials, but only the first and second trial blocks were administered in the current study due to time constraints.

The outcomes of interest from the ANT were reaction time on correct response trials averaged across congruent and incongruent flanker trials and the executive network score. The average reaction time was used as an index of attentional monitoring (see Costa et al., 2009). However, it should be noted that in the absence of reaction time data from a block of no conflict trials for comparison, participants' attentional monitoring scores from both the ANT and the Simon task the influence of perceptual or motor response speed cannot be excluded from this measure (see Paap & Greenberg, 2003). The executive network score was calculated by subtracting average reaction time on congruent trials from average reaction time on incongruent trials, which provides a classic measure of inhibitory control based on flanker interference (Eriksen & Eriksen, 1974) with a lower score indicating better inhibitory control.

Wisconsin Card Sorting Test: Participants completed the computerized version of the Wisconsin Card Sorting Test Computer Version 4 (Heaton & PAR staff, 2003). This task required participants to sort a set of test cards to match four target cards. Cards could be sorted on any of three dimensions (color, form, or number of forms). Participants were naïve

to the correct sorting dimension and instead relied on trial-and-error along with right/wrong feedback from the computer to identify the correct sorting rule. After participants correctly sorted a set number of consecutive cards using one sorting dimension, the sorting rule changed, and participants again used trial-and-error to determine the new sorting dimension. Testing continued until participants correctly sorted cards in six categories or sorted 128 cards. The score of interest from the WCST was participants' percentage of perseverative errors, which are errors that occurred when participants continued using a previously correct sorting dimension following a sorting rule change. Based on the findings of Miyake et al. (2000), the percentage of perseverative errors was assumed to measure participants' shifting ability. Refer to Table 1 for a summary of the EF components measured on each task.

Artificial language outcome measures: Participants' success in learning the small artificial language system was measured using six tests of receptive and expressive knowledge that were created for this study.

Vocabulary memory probe: The vocabulary memory probe was completed at the beginning of Session 2 in order to measure the nouns that participants retained from Session 1 (see description of procedure below). Participants viewed images of each noun from the artificial language and were asked to name each image. Responses were scored online as correct (all phonemes produced correctly or one phoneme error), incorrect (more than one phoneme error), and no response. Participants completed 12 trials corresponding to each noun in the artificial language.

Expressive vocabulary task: The expressive vocabulary task was identical in administration and scoring procedures to the vocabulary memory probe (described above), but this task was completed after artificial language training during Session 2.

Receptive vocabulary task: A receptive vocabulary task was used to assess comprehension of artificial language nouns. Participants viewed a page containing four images arranged in a grid, and chose the image that best represented the artificial language word read to them by the experimenter. There were 12 items in the receptive vocabulary task, corresponding to each of the nouns in the artificial language. Each page contained an image of the target noun, along with three incorrect foils. Scores on this task were calculated based on the percentage of correct responses with 25% correct indicating chance-level performance because each trial contained four possible response choices.

Expressive sentence task: The ability to produce sentences in the artificial language was measured using an expressive sentence task in which participants narrated 24 short animated videos – like those included in training – using the artificial language. Responses were scored online by the experimenter. The same scoring criteria applied to the expressive vocabulary task and vocabulary memory probe were used. Each item was scored for verb accuracy, noun-1 accuracy, and noun-2 accuracy. Those responses that contained two or more correctly produced words were also scored for word order accuracy. A composite score for the task was created based on the percentage of correct elements produced based on the total possible for each participant, which varied as a function of the number of items that could be scored for word order. No test animations used in the expressive sentence task were

included in the 300 training items; therefore, the task required participants to produce novel artificial language sentences.

Receptive sentence task: Participants completed a receptive sentence task to test their ability to comprehend sentences in the artificial language. In this task, participants heard a sentence in the artificial language as they viewed two animated videos, one of which correctly depicted the sentence (target) and one that did not correspond with the sentence (foil). Foil animations each included one of the following errors: incorrect verb, incorrect noun-1, incorrect noun-2, reversal of noun-1 and noun-2. Each of these error types occurred with equal frequency. After hearing the target sentence and viewing the two animations, participants indicated which animation depicted the sentence they heard. Participants completed 48 trials on the receptive sentence task. None of the sentences, target videos, or foil videos were included in the artificial language training videos. Scoring was based on the percentage of correct responses provided. Because this task required participants to choose a response between two alternatives, 50% accuracy represents chance-level responding.

Grammaticality judgment task: The final artificial language test was a grammaticality judgment task. The experimenter read a series of acceptable and unacceptable sentences in the artificial language, and participants rated whether each sentence was correct or incorrect. Half of the stimuli were correct productions (i.e., verb-noun-noun), and half were incorrect productions that violated the language's word order (e.g., noun-verb-noun, verb-verb-noun, verb-noun-verb, etc.). Participants completed 48 grammaticality judgment trials, and the experimenter recorded their responses. Sentences used in the grammaticality judgment task were not included in the artificial language training videos. Grammaticality judgment scores were calculated using an A' statistic, which is based on the proportion of false alarms (i.e., incorrectly accepting ungrammatical sentences) compared to the proportion of hits (i.e., correctly accepting grammatical sentences). An A' score of .50 indicates an inability to distinguish between grammatical and ungrammatical items, whereas a score of 1.0 represents perfect discrimination.

Procedure—Participants completed two hour-long experimental sessions that occurred between one and three days apart. A delay of at least one day occurred between the two sessions because previous research suggests that sleeping after exposure to new information improves learning outcomes (Gais, Lucas, & Born, 2006; Gomez, Bootzin, & Nadel, 2006). In Session 1, participants were asked to provide demographic information, the status of their hearing and vision, and previous second language experience. Next, participants began artificial language training.

Artificial language exposure began with noun training. The experimenter presented the participant with the book containing the 12 noun images. The experimenter named each item in the artificial language, and the participant immediately repeated the lexical item while looking at the picture. After noun training, participants watched 150 of the animated training videos (15 minutes total). Following artificial language training in Session 1, participants completed the PPVT-4, backward and forward digit span tasks, and computerized versions of the WCST, a visual Simon task, and the ANT.

During Session 2, participants began by completing the vocabulary memory probe, which measured the number of artificial language lexical items (nouns) that participants could recall from Session 1. Following this task, participants resumed artificial language training, during which they viewed a new series of training videos for 15 minutes. These 150 videos were different from those viewed during Session 1. After artificial language training was completed, participants' receptive and expressive knowledge of the language was measured using the previously described outcome measures in the following order: expressive vocabulary task, receptive vocabulary task, expressive sentence task, receptive sentence task, and grammaticality judgment task.

Results

Preliminary Analyses—Descriptive statistics were calculated for participant characteristics and performance on the PPVT-4, digit span, and EF measures. These descriptive statistics are presented in Table 2. The majority of participants (97.4%) had received some academic exposure to an L2 at the time of testing. The average self-reported proficiency rating for L2 was 2.0, which corresponds with 'fair'; the average self-reported proficiency rating for an L3 was 2.0 or 'fair'; and the average self-reported proficiency rating for an L4 was 1.7 (i.e., between 'poor' and 'fair'). These self-reported proficiency ratings support the monolingual status of participants. Participants' average scores on the expressive artificial language tasks was significantly greater than zero and artificial language receptive task performance exceeded chance level responding (refer to Methods) for each task (all $ps < .001$), which suggests that participants were generally successful in learning the artificial language. Within the expressive sentence task, participants were significantly better at producing both noun 1 and noun 2 than verbs, $t(78) = -4.97, p < .001$ and $t(78) = -4.91, p < .001$.

Principal Components Analysis—In order to reduce the number of variables included in subsequent regression analyses, principal components analysis was used to analyze artificial language outcome measures, which resulted in all variables loading on a single factor (all loadings $> .40$). This factor accounted for 68.5% of the variance in artificial language outcome measures (eigenvalue = 4.1). Bartlett's Test of Sphericity was significant, $\chi^2(15) = 338.25, p < .001$, and Kaiser's measure of sampling adequacy was .83. Refer to Table 3 for artificial language factor loadings. It is somewhat unexpected that all artificial language tasks loaded on a single factor, but it is possible that because of the simplicity of the language, participants were relying on vocabulary knowledge when completing all artificial language outcome tasks.

Multiple Regression Analyses—Hierarchical multiple regression analyses were run to determine the amount of variance in participants' artificial language factor scores that was predicted by their performance on the EF measures after controlling for the influence of English verbal ability (PPVT-4) and working memory (digit span). Changes in R^2 statistics were used to identify whether the amount of variance in the outcome predicted by the independent variables increased between the control model and the subsequent models that include both the control variables and EF predictors. Partial correlations were calculated to identify the amount of variance in each outcome explained by individual predictors.

Prior to conducting regression analyses, Mahalanobis distances were calculated for the independent variables and no significant multivariate outliers were identified in the data as no participants' Mahalanobis distance was significant based on the χ^2 distribution ($p > .001$). Additionally, residual histograms and scatter plots confirmed that the data were relatively normally distributed, linear, and residual distribution was homoscedastic.

Control model: The control model included PPVT and digit span as predictors, with the artificial language factor score as the outcome measure. This control model accounted for a significant amount of variance ($R^2 = .326$, $p < .001$) in the artificial language outcome factor. Both PPVT and digit span were significant positive predictors of the artificial language outcome score, indicating that participants with higher English receptive vocabulary and working memory spans also received higher scores on the artificial language outcome measures. Refer to Table 4 for a summary of regression analyses.

Model 1: The influence of the scores of interest from each EF measure on the artificial language outcome score, over and above receptive vocabulary and working memory was assessed by adding these scores as predictors in the second step of the regression analyses and measuring the change in R^2 between the two models. The addition of EF scores did not significantly increase the amount of variance explained beyond the control model (see Table 4). Within Model 1, participants' PPVT-4 and digit span scores were significant positive predictors of artificial language outcomes and ANT executive network performance was a significant negative predictor of outcomes. These significant predictors were retained in Model 2 and all non-significant predictors were removed from the model.

Model 2: Model 2 is a simplified model that includes the control model in the first step along with ANT executive network, which was the only significant EF predictor in Model 1, in the second step. This model accounted for a significant amount of variance in the artificial language outcome measure ($R^2 = .360$, $p < .001$) and resulted in a significant change in R^2 compared to the control model ($R^2 = .066$, $p < .01$). The ANT executive network score was a significant negative predictor of artificial language outcomes. This finding indicates that individuals with lower ANT executive network (i.e., better inhibitory control) scores had higher artificial language outcome scores.

Study 1 Discussion

The goal of Study 1 was to determine whether English monolingual adults' ability to acquire an artificial language system is predicted by their English receptive vocabulary knowledge and working memory capacity, and furthermore whether EF abilities are predictive of artificial language learning outcomes over and above these skills. After a total of 30 minutes of video training, adult participants successfully learned to produce and understand the simple artificial language system. Participants' performance on tasks that required production of the language was significantly above zero, and they performed above chance levels on measures of receptive artificial language knowledge.

As hypothesized, participants' English verbal ability and working memory span significantly predicted their success in learning a novel artificial language. Within the control regression

model, both PPVT-4 (i.e., English receptive vocabulary) and digit span (i.e., working memory) were significant positive predictors of scores on the artificial language outcome factor. These findings converge with previous L2 research that provides evidence of a positive relationship between L1 verbal ability (Sparks, Patton, & Ganschow, 2012) and verbal short term memory (Atkins & Baddeley, 1998; Martin & Ellis, 2012) and L2 acquisition.

Also as predicted, EF abilities were predictive of participants' artificial language-learning outcomes. However, this relationship did not emerge for the majority of our EF measures, as the ANT executive network score was the only significant predictor of artificial language learning after controlling for English receptive vocabulary and working memory. This ANT score is thought to measure participants' inhibitory control abilities. The relationship between participants' ANT executive network score and artificial language outcomes was negative, such that individuals with a lower ANT executive network score (i.e., better inhibitory control) were better artificial language learners (see Salthouse, 2010 for limitations of using flanker tasks to measure individual difference in inhibitory control). It is interesting to note that previous research has found that bilinguals have lower (i.e., better) ANT executive network scores than monolinguals (Costa et al., 2008), which has been used as evidence of an inhibitory control advantage for bilinguals. It is possible, however, that because of the documented relationship between working memory and the ANT executive network score (Redick & Engle, 2006) and inhibitory control more broadly (Unsworth, Fukuda, Awh, & Vogel, 2014), if a more complex working memory task (e.g., operation span) had been used, the predictive power of ANT executive network may have been attenuated or eliminated. In other words, there may be significant overlap between the executive function components of working memory and inhibitory control. Thus, based on the current data, we can conclude that inhibitory control appears to be predictive of artificial language learning independent of participants' performance on a simple-span measure of working memory.

We speculate that this relationship between inhibitory control and language learning may be related to the ability to inhibit English during artificial language learning and testing. Because the artificial language system used in this study had real-world referents with clear English translations (e.g., bird), it may be the case that individuals who were better able to avoid accessing English were in turn more successful learners. This is consistent with research with bilingual participants that suggests the need for inhibitory control to separate their two languages (particularly while using the weaker of their two languages; Meuter & Allport, 1999), and with evidence that L2 learners inhibit their L1 (Linck et al., 2009).

An alternative possibility is that participants were using inhibition within the context of the artificial language instead of between English and the artificial language (i.e., across languages). For example, participants had to inhibit accessing an incorrect but possible target in the language (e.g., elephant) when hearing an artificial language label (e.g., *nɜrk*). Likewise participants may have been inhibiting production of a non-target label (e.g., *nɜrk*) in response to a different referent within the artificial language (e.g., elephant). It is unclear within the current study at which level – within or across languages – the inhibition was

necessary for successful performance. Future research manipulating the level of interference from within or across languages may shed light on this issue.

STUDY 2

The goal of Study 2 was to determine whether the relationship between EF and artificial language learning established for adult participants in Study 1 extends to young, preschool-age children. Children in this study completed similar EF testing (modified for their younger age) and were exposed to the same artificial language used with adults in Study 1. Past research suggests that the process of language learning differs between children and adults for both natural (Krashen, Long, & Scarcella, 1979) and artificial languages (Hudson Kam & Newport, 2005). Therefore, it is possible that the nature of the relationship between EF and artificial language learning will differ between adult and child participants.

Method

Participants—Participants in Study 2 included 44 children (19 female) between the ages of 4;0 and 5;11 (mean age 4;8). Two children were tested but were removed from the final sample due to failure to complete the ANT as a result of child refusal ($n = 1$) or experimenter error ($n = 1$) resulting in a final sample of 42 participants. All children were reported by parents to speak a single language (English) fluently at the time of testing. Ten children were reported to regularly hear a non-English language, but these children received less than one hour of non-English language exposure each day and were unable to speak the language fluently. Parent report also confirmed that participants had normal or corrected-to-normal vision and hearing.

Artificial Language—The child participants in Study 2 were exposed to the artificial language used with adult participants in Study 1 via the same training videos described above.

Measures

Peabody Picture Vocabulary Test – 4: English receptive vocabulary was measured using the Peabody Picture Vocabulary Test—Fourth Edition (PPVT-4; Dunn & Dunn, 2007).

Digit span: Working memory was measured using forward and backward digit span tasks. Refer to Study 1 for task description. Again, forward and backward span scores were summed to create the digit span score used in all analyses.

Visual Simon task: Child participants completed the same visual Simon task used with adults in Study 1. All children were administered the test via E-Prime 2.0 (Schneider et al., 2002). To make the task suitable for children, the response window was extended to 5000ms or until participants made a response and target keys were labeled with blue and red stickers. A Simon effect score was calculated for each participant by subtracting their response accuracy on incongruent trials from accuracy on congruent trials, which serves as an index of inhibitory control. Participants' reaction time averaged across both congruent

and incongruent Simon trials (correct responses only) provided a measure of attentional monitoring.

Attention Network Test: Participants completed the Attention Network Test modified for children (Rueda et al., 2004). This task maintains the same characteristics of the adult version (described in Study 1), but target arrows are replaced with fish to make the task more engaging for young children, children receive correct/incorrect feedback following each trial, and each trial block contains only 48 trials. We further modified the task for the young participants by increasing the response time window to 3400ms. Participants completed 24 practice trials followed by one test block of 48 trials. The first outcome of interest from the ANT was RT (ms) averaged across congruent and incongruent trials, which provides an index of children's attentional monitoring abilities. The second outcome of interest was the ANT executive network score, which is calculated by subtracting accuracy on incongruent trials from accuracy on congruent trials and provided a measure of children's inhibitory control.

Dimensional Change Card Sort: Children's attentional shifting ability was tested using the DCCS (Zelazo, Frye & Rapus, 1996). Children first completed the standard version of the DCCS. Participants received a set of 12 test cards with images that varied on the dimensions of color and shape (e.g., red rabbits and blue cars). Two sorting bins were placed in front of the participant, each labeled with a target card (e.g., blue rabbit and red car). In the pre-switch phase of the task, children sorted the test cards with the target cards using one of the two dimensions (e.g., color) by placing cards face down in boxes. After children sorted six cards, the experimenter informed them that the game changed. In this post-switch phase, children sorted the remaining six cards using the opposite dimension (e.g., shape). The experimenter reminded children of the sorting dimension before each trial (e.g., 'Remember in the shape game, all the bunnies go here and all the cars go here. Here is a car. Where does it go?'). In order to succeed on the post-switch phase, children must shift their attention to the new relevant dimension while simultaneously inhibiting attention to the previous sorting dimension. Each participant received a pre-switch score based on the number of cards correctly sorted during pre-switch sorting (0–6) and a post-switch score reflecting the number of correctly sorted cards following the sorting dimension change (0–6).

Those children who passed post-switch sorting (i.e., correctly sorted five out of six post-switch cards) in the standard DCCS completed the advanced version of the DCCS (Carlson, 2005; Zelazo, 2006). The advanced version of the task maintains the same target cards used in the standard task, but half of the 12 test cards have a black rectangular border surrounding the image. Children were instructed to sort the cards with a border by one dimension (e.g., color), and to sort the cards without borders using the other dimension (e.g., shape). The border cards were randomly intermixed within the deck of test cards, so children were unaware of when a sorting dimension switch would occur. Again, children were reminded of the rules of the game as the experimenter gave them each card (e.g., 'Remember, if there is a border play the color game and if there is no border play the shape game. This card has a border. Where does it go?'). Children's advanced DCCS scores were the number of test cards correctly sorted (0–12). The DCCS provides an index of children's attentional shifting

ability, or their ability to switch attention between relevant stimulus dimensions. The specific EF components assessed by each measure in Study 2 are summarized in Table 5.

Artificial language outcome measures: Participants' success in learning the small artificial language system was measured using same six tests of receptive and expressive artificial language knowledge that were created for Study 1. Identical tasks and administration procedures used with adults in Study 1 were used with child participants in Study 2 for the following measures: vocabulary memory probe, expressive vocabulary task, and receptive vocabulary task. The same expressive sentence task and receptive sentence task used with adults in Study 1 were also employed in Study 2, but children only completed 12 items on the expressive sentence task and 24 receptive sentence task trials. Finally, to make the grammaticality judgment task more engaging for children, they were introduced to a puppet whom they were told was also learning the artificial language. Participants were asked to help him practice by telling him when his utterances sounded "good" versus "not so good." The child version of the grammaticality judgment task included 24 trials. Half of the trials included acceptable sentences in the artificial language and half included unacceptable sentences.

Procedure—Children completed two one-and-a-half-hour experimental sessions. In Session 1, parents/guardians answered basic demographic questions, confirmed that their child's hearing and vision were normal or corrected-to-normal, and reported any languages that the child spoke fluently or heard regularly. Children were introduced to an alien puppet, and the experimenter explained to that they were going to learn the alien's language. Artificial language exposure began with an introduction to the nouns. The experimenter presented the child with a book containing 12 images representing the 12 nouns in the artificial language with one image on each page. The experimenter produced the artificial language label for each item and children immediately repeated the label. This procedure was repeated four times for a total of four exposures to each noun.

Following noun training, children watched the same artificial language training videos used in Study 1. Children watched the training videos for a total of 30 minutes in Session 1; taking breaks every 10 minutes or as needed. In 30 minutes, children viewed 300 short animated videos (6 seconds), each depicting a unique sentence in the artificial language. Following artificial language training, children completed the PPVT-4, forward and backward digit span measures, the DCCS, the Simon task, and the ANT.

Session 2 occurred between one and four days after Session 1 and began with a memory probe to measure which artificial language nouns the children could produce from Session 1. After asking children to name each of the 12 nouns in the vocabulary memory probe procedure, the experimenter presented the 12 nouns again and asked that children repeat their artificial language names. Participants' responses were audio recorded during the vocabulary memory probe for future scoring and their repetitions of the noun labels were also recorded. These recordings of repetitions were then used as baseline correct responses for scoring expressive language tasks in order to account for any systematic articulation errors during task scoring.

Following noun training, children viewed the same series of 300 video segments from Session 1 presented in a different order. Again, children viewed the videos for a total of 30 minutes. After language training was completed, participants completed artificial language testing in the following order: expressive vocabulary test, receptive vocabulary test, expressive sentence test, receptive sentence test, and grammaticality judgment task.

Results

Preliminary Analyses—Descriptive statistics were calculated for participant characteristics and performance on the PPVT-4, digit span, and EF measures. These descriptive statistics are presented in Table 6. Participants' average scores on the expressive artificial language tasks were significantly greater than zero, and they exceeded chance level responding on both the receptive vocabulary and grammaticality judgment task (all p s < .01). However, children's performance on the receptive sentence task did not exceed chance-level responding, $t(41) = 1.64$, $p = .11$. Within the expressive sentence task, children were significantly more accurate in producing noun 1 and noun 2 compared to verbs, $t(41) = -10.53$, $p < .001$ and $t(41) = -9.85$, $p < .001$.

Principal Components Analysis—A principal components analysis of artificial language outcomes resulted in a single factor solution with all six artificial language variables loading on one factor, which accounted for 53.1% of the variance in artificial language outcome measures (eigenvalue = 3.2). Bartlett's Test of Sphericity was significant, $\chi^2(15) = 107.33$, $p < .001$, and Kaiser's measure of sampling adequacy was .78. Refer to Table 7 for artificial language factor loadings. As was the case in Study 1, all artificial language measures loaded on a single factor, which again may result from the underlying role of vocabulary knowledge in performance on all tasks.

Multiple Regression Analyses—Hierarchical multiple regression was used to determine the amount of variance in participants' artificial language factor scores that was predicted by their performance on the EF measures after controlling for the influence of English verbal ability (PPVT-4) and working memory (digit span). Prior to conducting regression analyses, Mahalanobis distances were calculated for the independent variables and no significant multivariate outliers were identified in the data as no participants' Mahalanobis distance was significant based on the χ^2 distribution (p s > .001). Additionally, residual histograms and scatter plots confirmed that the data were relatively normally distributed, linear, and residual distribution was homoscedastic.

Control model: The control model included PPVT and digit span as predictors, with the artificial language factor score as the outcome measure. This control model accounted for a significant amount of variance ($R^2 = .193$, $p < .05$) in the artificial language outcome factor. Digit span performance was a significant positive predictor of the artificial language outcome factor, indicating that participants with higher working memory spans received higher scores on the artificial language outcome measures. Children's PPVT-4 performance was not significantly predictive of their artificial language outcomes. Refer to Table 8 for a summary of regression analyses. Although children's receptive vocabulary score was not a significant predictor within the control model, this variable was retained in step one of

subsequent regression models because our hypotheses were based on models that control for the influence of both working memory (digit span) and vocabulary. Furthermore, retaining PPVT performance as a predictor maintains consistency between our analyses in Study 1 and Study 2 in order to facilitate comparisons between adult and child participants across the two studies.

Model 1: The influence of the scores of interest from each EF measure on the artificial language outcome factor, over and above receptive vocabulary and working memory was assessed by adding the EF scores in the second step of the regression analyses and measuring the change in R^2 . Model 1 accounted for a significant amount of variance ($R^2 = .424$, $p < .01$) in the artificial language outcome factor. The addition of EF scores significantly increased the amount of variance explained beyond the control model ($R^2 = .230$, $p < .05$). Within Model 1, participants' ANT reaction time and their DCCS score were significant predictors of artificial language outcomes.

Model 2: Model 2 is a simplified model that includes the control model in the first step along with only those executive function measures that were significant predictors in Model 1 – ANT reaction time and DCCS score – in the second step. This model accounted for a significant amount of variance in the artificial language outcome measure ($R^2 = .360$, $p < .01$) and resulted in a significant change in R^2 compared to the control model ($R^2 = .167$, $p < .05$). Neither PPVT-4 nor digit span were significant predictors of artificial language outcomes in Model 2. Participants' ANT reaction time was a marginally significant negative predictor in the model, such that children with faster ANT RT had higher artificial language outcome factor scores. The DCCS score was a significant positive predictor of performance on artificial language tasks indicating that children with better scores on a card sorting task performed better on artificial language outcome measures.

Study 2 Discussion

The goal of Study 2 was to determine whether preschoolers' ability to acquire an artificial language system was predicted by their EF ability after controlling for the effects of their native language vocabulary and working memory abilities. After a total of 60 minutes of artificial language training, child participants successfully learned to produce and understand much of the simple artificial language system. Participants' performance on tasks that required production of the language was significantly above zero, and they performed above chance levels on the receptive vocabulary and grammaticality judgment tasks. However, child participants did not learn to produce the artificial language's verbs, nor did they perform above chance on the receptive sentence task. These results suggest that children were able to learn the explicitly taught nouns, but were less successful in acquiring the artificial language's verbs or word order, which both had to be learned implicitly from video training stimuli.

As hypothesized, participants' working memory span significantly predicted their success in acquiring the artificial language. Children with better working memory skills as indexed by digit span measures were more successful in learning the novel artificial language. However, counter to predictions, children's English receptive vocabulary (PPVT-4) was not

significantly predictive of their ability to acquire the artificial language. Because of the simplicity of the artificial language system, the task of learning the language was largely one of vocabulary learning; therefore, the lack of relationship between children's English vocabulary abilities and their artificial language outcomes is somewhat surprising. However, it is possible that children were largely learning the artificial language vocabulary through explicit learning mechanisms, whereas, their English vocabulary is primarily acquired implicitly, which may explain why these variables were unrelated. In support of this possibility is the fact that children were only successful in learning the artificial language nouns that were explicitly taught and were unable to learn the verbs, which had to be implicitly acquired.

Also as hypothesized, children's EF abilities were predictive of their artificial language-learning outcomes after controlling for working memory and English receptive vocabulary. However, this relationship did not emerge for the majority of our EF measures, as performance on the DCCS was the only significant predictor of artificial language learning, while ANT average RT was a marginally significant predictor.

Performance on the DCCS was positively associated with artificial language outcomes, and this task provides a measure of children's attention shifting abilities. Therefore, children who were better able to shift their attention between multiple stimulus dimensions while completing the DCCS were more successful language learners. Perhaps this relationship results from the fact that children who performed better on the DCCS were more successful in considering two possible labels for target items (i.e., both English and artificial language). In other words children who could shift between focusing on an object's shape and color on the DCCS were also better able to shift between considering an object a *frog* and a *nsrk*.

Participants' RT on ANT trials averaged across both congruent and incongruent flanker trials was a marginally significant negative predictor of artificial language learning. Reaction time on tasks that require switching between congruent and incongruent trials has been interpreted as a measure of attentional monitoring (Costa et al., 2009). In this case, children with faster RT, or better attentional monitoring, were more successful artificial language learners, perhaps due to their improved ability to attend to multimodal artificial language input during video training. Previous research has reported that bilingual children outperform monolinguals on both the DCCS (Bialystok, 1999; Bialystok & Martin, 2004) and the ANT (Kapa & Colombo, 2013; Yoshida et al., 2011), suggesting that these tasks measure executive function skills that may be enhanced through bilingual experience.

General Discussion

The general finding of the present studies – that individuals with better EF were more successful in learning the artificial language – has potentially interesting implications for evaluating evidence of bilingual advantages in EF. The current findings suggest that both children and adults with better EF abilities may be advantaged language learners; therefore, it is possible that those individuals who achieve high levels of L2 proficiency are more skilled in EF prior to acquiring an L2. That is, in selecting highly proficient bilinguals to include in their samples, researchers may also be selecting individuals who had relatively

strong EF abilities before they began speaking an L2. This does not imply, however, that L2 learning has no effect on EF. Rather, it is likely the relationship between EF and language-learning is bidirectional, such that individuals with better EF are better language-learners, and experience controlling two language systems improves domain-general EF abilities. Future research should further examine this possible bidirectional relationship between EF and language learning.

Comparing across the results of Study 1 and Study 2, we find that EF abilities are predictive of artificial language learning for both adults and preschool children. However, the specific EF components that are related to artificial language learning vary across the two groups. Among the adults tested in Study 1, inhibitory control was a significant predictor of artificial language outcomes, whereas in Study 2, preschoolers' language outcomes were predicted by attentional shifting and to some degree attentional monitoring abilities. One possible source of the group differences may be that adults are relying more than children on translation between English and the artificial language, a strategy that has been reported among adult L2 learners (Kroll & Tokowicz, 2001). This may explain why English vocabulary was predictive of artificial language learning for adults but not children and likewise why inhibition may be predictive of adults' outcomes. If adults indeed learned the artificial language through translation, then they would need an inhibition mechanism to avoid accessing the salient English counterparts during language testing. The relationship between inhibition and artificial language learning for adults converges with evidence that inhibition plays an important role in L2 learning (Linck et al., 2009; Wang et al., 2007).

Based on the study outcomes, the role of attentional shifting and monitoring in artificial language learning seems to be limited to children. This may be due to the need for children to accept two labels for objects (i.e., English and the artificial language), which would require overriding the mutual exclusivity assumption the each entity has one label (Markman, 1990; Merriman & Bowman, 1989). This task may be easier for children with stronger attentional shifting abilities because they are better equipped to simultaneously consider multiple object properties and shift their attention between them. The ability to shift attention between dimensions, as indexed by DCCS performance, has been found to be advantaged among bilingual children (Bialystok, 1999; Bialystok & Martin, 2004), which may similarly be related to their experience shifting attention between two languages.

Finally children's attentional monitoring was a marginally significant predictor of artificial language learning, but this was not true of adults. This relationship may be due to differences in attending to stimuli. Children with better attentional monitoring may have been more successful in attending to the changing stimuli in training materials compared to peers with less efficient attentional monitoring. This ability may have been a less important factor for adults' language learning outcomes because adults have more mature attentional systems and less individual variability in attentional monitoring compared to children. Within the current study, the standard deviation for ANT reaction time was 57.5ms among adults and 259.8ms in the child sample. Attentional monitoring as measured by ANT reaction time performance has been previously reported to be advantaged among bilingual children (Kapa & Colombo, 2013) and adults (Costa et al., 2009), which again highlights the relationship between this EF component and language-learning.

It is important to note that although these findings have interesting potential implications for the relationship between EF and L2 learning, they cannot be easily extended to natural language-learning as the current pattern of results may be restricted to artificial language learning within a laboratory setting. Furthermore, these results may be limited to the type of highly simplified language used here. Because of the impoverished syntax (only linear word order) and lack of morphology, the task of acquiring the artificial language was largely one of vocabulary learning. Thus, the relationship between artificial language learning and EF reported here may be more narrowly a relationship between EF and vocabulary learning. If this is the case such a relationship is interesting nonetheless, as vocabulary learning is a crucial element in the process of L2 acquisition, particularly during the earliest stages of acquisition.

One interesting note is the unexpected discrepancy between results on the ANT and the visual Simon task. These tasks were expected to index the same EF components: inhibitory control and attentional monitoring, however, participants' performance on these tasks was not correlated. Furthermore, ANT performance was predictive of artificial language learning for both adults and children, while Simon performance was unrelated. There are multiple possible explanations for this discrepancy. The first is that the visual Simon task used here, which was based on the task employed by Bialystok et al. (2004), may have included too few trials to provide a stable measure of these EF components. Furthermore, our procedure of randomization of congruent and incongruent trial presentation in the Simon task may have reduced its utility as a measure of individual differences. Additionally, a computerized visual Simon task may be a less reliable executive function measure in general, as Sawi and Paap (2003) report poor test-retest reliability for this measure. This specific case of discrepancy in outcomes between two executive function measures that are thought to measure the same constructs illustrates the challenges of defining and measuring executive function. Indeed, there is ongoing debate regarding the extent to which executive function components are separable, and which, if any, tasks can provide pure measures of these individual components.

Conclusion

The goal of the present studies was to establish whether adults' and children's EF skills are predictive of their ability to learn a simple artificial language system. Previous research has established a relationship between L2 acquisition and EF, such that individuals who become proficient and balanced bilinguals demonstrate advantages over monolinguals on non-verbal measures of EF. In the present study, we considered the possibility that individuals with better EF abilities may in turn be more successful language learners. After controlling for participants' English receptive vocabulary and working memory span, adults' artificial language learning outcomes were significantly predicted by their performance on the ANT executive network score, which assesses inhibitory control. Among children, artificial language outcomes were significantly predicted by their performance on the DCCS, which is a measure of attentional shifting, and marginally significantly predicted by their ANT reaction time, which indexes attentional monitoring.

Thus, the current study provides initial evidence that both adults and children are indeed using EF processes when acquiring a novel artificial language. However, the underlying EF components that appear to be involved in artificial language learning differ between the age groups. It is unclear whether the current findings extend beyond artificial languages to natural language learning, and further due to the simplicity of the artificial language used here, these relationships may be restricted specifically to the process of vocabulary learning. Future research examining whether this relationship exists between EF and natural L2 acquisition is warranted. Additionally, if EF is found to be predictive of natural L2 learning outcomes, then it may be possible to integrate EF training, which is becoming increasingly popular (Diamond & Lee, 2011; Hussey & Novick, 2012; Posner & Rothbart, 2005; Rueda, Rothbart, McCandliss, Saccomanno, & Posner, 2005; Tang & Posner, 2009), along with language instruction in order to improve individuals' language learning outcomes.

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Appendix A. Artificial Language Lexical Items

Nouns	Gloss	Verbs	Gloss
/nsrk/	frog	/blt/	move under
/nagrɔ/	elephant	/smt/	move beside
/nagrʌ/	rhinoceros	/flm/	move around
/ædnʌ/	turtle	/lks/	move on top
/msnʌ/	snake		
/msrnt/	boy		
/fɜrlukʌ/	girl		
/fumpogʌ/	bird		
/slɜrgʌn/	alligator		
/flugat/	bee		
/tombat/	giraffe		
/blɜrgən/	lion		

Table 1

Executive Function Components Measured on each Task in Study 1

Task	Score	EF Component
Simon	RT averaged across congruent and incongruent trials	Attentional Monitoring
Simon	Simon effect ^a	Inhibitory Control
ANT	RT averaged across congruent and incongruent trials	Attentional Monitoring
ANT	Executive Network ^a	Inhibitory Control
WCST	Percentage perseverative errors	Shifting

^aincongruent RT - congruent RT

Table 2

Study 1 Descriptive Statistics

Measure	Mean	Std. Deviation	Range
Age (mo.)	235.5	15.7	220 – 332
Days between Sessions	1.8	.69	1 – 3
PPVT	105.8	12.9	81 – 135
Forward Digit	10.9	1.7	8 – 14
Backward Digit	7.7	2.1	2 – 12
WCST Perseverative Errors	.10	.05	.05 – .28
Simon Effect (ms)	16.4	37.7	–76 – 115
Simon Average RT (ms)	425.7	56.5	322 – 619
ANT Executive Network (ms)	107.9	38.7	45 – 307
ANT Average RT (ms)	507.3	57.5	414 – 715

Table 3

Study 1 Factor Loadings (Principal Components Analysis) of Artificial Language Outcome Measures

Measure	Factor 1
Memory Probe	.63
Expressive Vocabulary	.88
Receptive Vocabulary	.77
Expressive Sentence Task	.92
Receptive Sentence Task	.86
Grammaticality Judgment Task	.87

Note. Factor loadings > .40 are in boldface.

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Table 4
Study 1 Regression Model Predicting Scores on the Artificial Language Outcome Factor

Measure	R^2	Cumulative R^2	Adjusted R^2	s^2	β	t
Control	.294***	.294***	.275***			
PPVT				.390	.370	3.70**
Digit				.332	.307	3.07**
Model 1	.083	.376***	.315***			
PPVT				.362	.353	3.27**
Digit				.235	.220	2.04*
Simon Effect				-.066	-.053	-.553
Simon RT				-.137	-.127	-1.17
ANT Executive				-.260	-.262	-2.27*
ANT RT				.010	.010	.082
WCST Perseverative				-.040	-.036	-.339
Model 2	.066**	.360***	.335***			
PPVT				.378	.342	3.54**
Digit				.296	.261	2.68**
ANT Executive				-.307	-.265	-2.79**

Note:

$\dagger$ p .10.
* p .05.
** p .01.
*** p .001.

Table 5

Executive Function Components Measured on each Task in Study 2

Task	Score	EF Component
Simon	Median RT across congruent and incongruent trials	Attentional Monitoring
Simon	Simon effect ^a	Inhibitory Control
ANT	Median RT across congruent and incongruent trials	Attentional Monitoring
ANT	Executive Network ^a	Inhibitory Control
DCCS	Total cards correctly sorted ^b	Shifting

^a congruent accuracy - incongruent accuracy;

^b summed across standard version pre-switch, post-switch, and advanced version (0 – 24)

Table 6

Study 2 Descriptive Statistics

Measure	Mean	Std. Deviation	Range
Age (mo.)	56.9	6.7	48 – 71
Days between Sessions	1.9	.77	1 – 4
PPVT	119.3	12.1	91 – 146
Forward Digit	5.2	1.5	2 – 8
Backward Digit	1.7	1.3	0 – 4
DCCS Pre-switch	6.0	.15	5 – 6
DCCS Post-switch	5.5	1.6	0 – 6
DCCS Advanced	6.6	2.9	0 – 11
Simon Effect (accuracy)	.02	.12	–.29 – .36
Simon Average RT (ms)	1272.3	317.0	678 – 2159
ANT Executive Network (accuracy)	.07	.20	–.31 – .75
ANT Average RT (ms)	1473.5	259.8	948 – 2064

Table 7

Study 2 Factor Loadings (Principal Components Analysis) of Artificial Language Outcome Measures

Measure	Factor 1
Memory Probe	.76
Expressive Vocabulary	.89
Receptive Vocabulary	.82
Expressive Sentence Task	.91
Receptive Sentence Task	.40
Grammaticality Judgment Task	.39

Note. Factor loadings > .40 are in boldface.

Table 8
Study 2 Regression Model Predicting Scores on the Artificial Language Outcome Factor

Measure	R^2	Cumulative R^2	Adjusted R^2	β	t
Control	.194 [*]	.194 [*]	.153 [*]		
PPVT			.000	.000	.001
Digit			.410	.440	2.80 ^{**}
Model 1	.230 [*]	.424 ^{**}	.306 [*]		
PPVT			-.146	-.127	-.859
Digit			.145	.163	.855
Simon Effect			-.208	-.168	-1.24
Simon RT			.224	.191	1.34
ANT Executive			.010	.009	.057
ANT RT			-.366	-.345	-2.29 [*]
DCCS Total			.419	.432	2.69 [*]
Model 2	.167 [*]	.361 ^{**}	.292 [*]		
PPVT			-.070	-.062	-.426
Digit			.134	.142	.825
ANT RT			-.278	-.247	-1.76 [†]
DCCS Total			.399	.423	2.65 [*]

Note:

[†] p .10.
^{*} p .05.
^{**} p .01.