Statistically Based Chunking of Nonadjacent Dependencies

Erin S. Isbilen[1,2], **Rebecca L. A. Frost**[3,4], **Padraic Monaghan**[5,6], **Morten H. Christiansen**[1,2,7,8]

[1]Department of Psychology, Cornell University

[2]Haskins Laboratories, New Haven, Connecticut, United States

[3]Department of Psychology, Edge Hill University

[4]Language Development Department, Max Planck Institute for Psycholinguistics, Nijmegen, the Netherlands

[5]Department of Psychology, Lancaster University

[6]Amsterdam Center for Language and Communication, University of Amsterdam

[7]Interacting Minds Centre, Aarhus University

[8]School of Communication and Culture, Aarhus University

Abstract

How individuals learn complex regularities in the environment and generalize them to new instances is a key question in cognitive science. Although previous investigations have advocated the idea that learning and generalizing depend upon separate processes, the same basic learning mechanisms may account for both. In language learning experiments, these mechanisms have typically been studied in isolation of broader cognitive phenomena such as memory, perception, and attention. Here, we show how learning and generalization in language is embedded in these broader theories by testing learners on their ability to chunk nonadjacent dependencies —a key structure in language but a challenge to theories that posit learning through the memorization of structure. In two studies, adult participants were trained and tested on an artificial language containing nonadjacent syllable dependencies, using a novel chunking-based serial recall task involving verbal repetition of target sequences (formed from learned strings) and scrambled foils. Participants recalled significantly more syllables, bigrams, trigrams, and nonadjacent dependencies from sequences conforming to the language's statistics (both learned and generalized sequences). They also encoded and generalized specific nonadjacent chunk information. These results suggest that participants chunk remote dependencies and rapidly generalize this information to novel structures. The results thus provide further support for learning-based approaches to language acquisition, and link statistical learning to broader cognitive mechanisms of memory.

The natural world is awash with statistical regularities, from which individuals can glean the structure of the environment. Yet successful learning entails more than the acquisition of distinct instances from the input: it requires learners to use this information flexibly and extrapolate to novel situations. Investigations into how individuals learn and generalize have a long pedigree in psychology, spanning the domains of episodic learning (Bauer & Dow, 1994), vision and motor control (Poggio & Bizzi, 2004), and language (Wolff, 1982). However, the specific mechanisms and representations involved in these processes, and how individuals move from encoding individual items to forming category-based generalizations, remains an area of debate.

In recent years, one formative memory process has advanced to the frontlines of many discussions on learning across cognitive domains: chunking. Chunking has long been recognized as a foundational cognitive process, enabling the grouping of discrete elements into larger units to alleviate the limits of working memory—a major challenge to the human perceptual system (Cowan, 2001; Miller, 1956). It plays a key role in many higher level skills such as chess (Chase & Simon, 1973; Gobet & Simon, 1998) and the perception and production of language in real time (Christiansen & Chater, 2016). Chunking has even been implicated as a central component in one of the most powerful means of learning from the regularities present in the environment: statistical learning (e.g., Christiansen, 2019; Perruchet & Pacton, 2006).

Though often discussed as a single mechanism, and investigated in relative isolation from other psychological processes, the phenomenon known as statistical learning may actually comprise a suite of computations, with distinct cognitive processes handling different aspects of learning (Frost et al., 2015; Frost et al., 2019). Indeed, mounting evidence highlights the contributions of memory processes and of chunking, in particular, to statistical learning and the many behaviors for which it accounts. At a theoretical level, chunking has been defined as a mechanism by which distributional regularities are used to form discrete representations of an input, especially in the linguistic domain. Numerous chunking-based computational models can approximate human statistical learning of language-related distributional patterns (e.g., French et al., 2011; Perruchet & Vinter, 1998), illustrating how chunking can enable the cognitive system to combine co-occurring elements into larger units to represent specific items from an input (e.g., using the frequent co-occurrence of syllables "A" "B" and "C" to form the word "ABC"). Chunking models can also simulate children's natural language acquisition, comprehension and production by leveraging transitional probabilities to define multiword chunks—a finding which extends to numerous languages (McCauley & Christiansen, 2019a).

Behaviorally, chunking-based recall tasks can capture key results in statistical learning, including the landmark study by Saffran et al. (1996), which demonstrated that young infants can rapidly pick up on patterns of syllable co-occurrence in an artificial language consisting of trisyllabic nonsense words. In a recent study, after a brief exposure to a

similar artificial language, adult participants recalled syllable sequences that adhered to the statistics of the language significantly better than sequences containing the same syllables in a random order (Isbilen et al., 2020). Participants even recalled specific trigram syllable chunks (or words) from the artificial language, suggesting the involvement of chunking during statistical learning that enabled the representation of whole chunks of information. Similar results were obtained in a follow-up study with 5- to 6-year-old children (Kidd et al., 2020). Just as high-frequency chunks in natural language aid the retention of items in memory (e.g., recalling the letters *ciafbiusa* proves easier than recalling *uacfisbia*, as it contains the chunks "CIA," "FBI," and "USA"; Cowan, 2001), the chunking of novel statistical patterns confers comparable memory advantages by reducing cognitive load.

Despite the promise of the chunking account of statistical learning, supporting evidence is still critically limited. Most prior observations of statistically based chunking focus on the processing of adjacent regularities—that is, relationships between items that immediately follow one another in speech. Yet, language also contains dependencies between elements that do not occur directly next to one another in a sequence, and the learning of these structures necessitates more than rote memorization alone. These nonadjacent (or long-distance) dependencies are ubiquitous in many of the world's languages, allowing for flexible usage (e.g., *is_ing => is sitting, is always talking*; *un__ed => uncovered, uncensored, unrestrained*) and linguistic productivity—one of the hallmarks of human language (Hockett, 1959). From the viewpoint of statistical learning, such nonadjacent dependencies constitute reliable statistical relationships between elements that are separated by one or more intervening items (e.g., in the sequence AXC, A and C reliably co-occur but the identity of X varies). They can be learned at the item level (e.g., specific AXC combinations), as well as at the structural level (A–C pairings), along with the ability to generalize these structures to novel instances (e.g., AZC, where Z represents a new item that was not previously encountered in the A–C structure). Nonadjacent dependency learning thus provides a case study for the longstanding debate of how individuals move from encoding specific items to forming generalizations over them (Goldberg, 2006; Radulescu et al., 2020), and for determining whether these two abilities rely upon the same suite of statistical computations or require separate processes. It also provides a study of whether chunking is constrained to the grouping of adjacent relations, or if such memory processes are more flexible than previously assumed.

Several studies have successfully demonstrated that adults (e.g., Frost & Monaghan, 2016; Gómez, 2002; Peña et al., 2002; Perruchet et al., 2004; Romberg & Saffran, 2013), and infants (e.g., Frost et al., 2019; Gómez, 2002; Gómez & Gerken, 1999; Marchetto & Bonatti, 2013, 2015) can acquire nonadjacent dependencies using statistical learning. Indeed, infants as young as 6.5 months can leverage redundancy between nonadjacent syllables to boost recognition of trained target syllables (e.g., *ko ba ko*, where *ba* is the target syllable), suggesting that they are sensitive to noncontiguous information starting early in development (Goodsitt et al., 1984). However, the precise mechanisms subserving the acquisition of nonadjacent dependencies—and whether they differ from those used to learn adjacent dependencies—have been subject to much discussion, particularly regarding whether these computations draw on statistical learning processes alone or require more complex algebraic operations (see, e.g., Frost & Monaghan, 2016; Peña et al., 2002;

Perruchet et al., 2004). Although increasing evidence is converging on the notion that nonadjacent dependencies can be discovered via statistical learning (Wilson et al., 2020), the extent to which chunking is involved in this process remains highly contested (Endress & Bonatti, 2016).

Nonadjacent dependencies present a formidable challenge to theories that view learning as proceeding through the memorization and recognition of structure. In fact, there is limited evidence that nonadjacent information can be represented in memory as chunks at all, either by human learners or in computational models (e.g., French et al., 2011; Perruchet & Vinter, 1998). By definition, statistical chunking involves the grouping together of elements on the basis of co-occurrence statistics, and it is conceivable that this may extend to nonadjacent relations. However, Kuhn and Dienes (2005, p. 1418) have stated that "chunking models are very good at learning local dependencies but cannot learn nonlocal dependencies." Similarly, Bonatti et al. (2006, p. 320) have claimed that "much remains to be done before researchers can conclude that humans rely on chunking, as opposed to computing distant transitional probabilities, to capture nonadjacent relations among components of a continuous stream," with both accounts positing the acquisition and representation of rules rather than chunks.

The rule-based framework purports that the learning of words (e.g., AXC) and nonadjacent structure (e.g., A–C pairings) require separate mechanisms. According to this framework, although basic statistical computations are sufficient for acquiring individual AXC items from speech, learning A–C structural relations are thought to require complex, "algebraic" computations involving rule-like representations to enable generalization (Endress & Bonatti, 2007, 2016; Endress, Cahill, et al., 2009; Endress, Nespor, & Mehler, 2009; Peña et al., 2002). This account further suggests that positional memory mechanisms may be sufficient to explain sensitivity to nonadjacent dependencies (Endress & Bonatti, 2016), with syllables at the edges of these structures being encoded rather than the nonadjacent structure as a whole (Endress & Bonatti, 2007; Endress & Mehler, 2009). By these views, statistically based chunking is insufficient to account for the behavioral data, and chunked representations are rejected in favor of rules and the memorization of ordinal position. These theories parallel classical linguistic frameworks, which posit that statistical computations are insufficient for language acquisition (Chomsky, 1957, 1980), which must instead rely on symbolic grammatical inference to generalize beyond the limited exemplars in the input.

The question of how nonadjacent structures are represented has been the focus of much attention. Understanding these representations is of particular importance, as it is from the data of studies targeted to probe these representations that researchers often infer the nature of the computations employed during learning and generalization. Findings from the chunking literature suggest a possible role for chunking in learning nonlocal structures—a finding that would be expected if such memory processes are indeed integral to learning at large. For instance, various studies of artificial grammar learning (AGL; see Perruchet, 2019 for a review), which have strong parallels with statistical learning approaches, have demonstrated the central role of chunk strength (the relative frequency with which bigrams or trigrams in a test item occurred together during training; Knowlton & Squire, 1994, 1996) in the learning of simple, variable grammars while discounting the acquisition of rules (Kinder & Assmann, 2000). Indeed, chunking models appear well suited to capturing human

statistical learning representations in the linguistic domain (e.g., Frank et al., 2010; Giroux & Rey, 2009), and in the spatial domain (Orbán et al., 2008), where information is not necessarily contiguous.

Importantly, the chunking perspective makes specific predictions about both the computations and representations involved in statistical learning. Based on statistical regularities, the chunking process combines recurring items into larger units online during learning. This leads to the formation of concrete, chunked representations of the input, such as words, phrases, or multiword units that can be used to formulate novel constructions (e.g., McCauley & Christiansen, 2019a). These ideas relate to usage-based frameworks within the study of language acquisition (e.g., Goldberg, 2006; Lieven et al., 1997; Tomasello, 2003), where learners are thought to acquire specific items from the input through experience, which serve as the foundation for generalization and productivity. Unlike classical linguistic theories, such exemplar-based learning is not language-specific but is thought to apply across cognitive domains.

To reappraise the relationship between acquisition and generalization, and the role of memory therein, the current article employs the statistically induced chunking recall task (SICR; Isbilen et al., 2020), using nonadjacent dependency learning as a test case. SICR presents both statistically legal items (composed of two trisyllabic target words) and illegal strings (the same syllables randomized) from a trained artificial language, which participants are asked to recall out loud in the correct order. If participants have chunked the input language into individual words during training (e.g., *abc-def* => "abc" "def"), then recall of the trained items should yield significantly higher accuracy than recall of the random strings (e.g., *efbdca*). Furthermore, as the SICR data is transcribed then scored syllable by syllable, it is possible to directly examine participants' representations in a manner that standard forced-choice tasks do not afford. The more detailed memory-based measures of SICR thus provide specific insights into the representations formed during processing. Participants' productions can be analyzed for specific chunk formation—recall of full words from the trained target strings, and in the present case, recall of full nonadjacent dependencies. Sensitivity to statistical structure can thus be measured by comparing recall of the target strings to recall of the foils, which serve as a baseline working memory measure.

The SICR paradigm is modeled on key findings from the memory literature which indicate that immediate recall abilities are fundamentally shaped by long-term distributional learning. For instance, nonwords that adhere to the phonotactic patterns that occur regularly in natural speech are recalled more accurately than those based on infrequent phoneme sequences (Gathercole et al., 1999), and high-frequency digit combinations are recalled more accurately than lower probability numerical sequences (Jones & Macken, 2015; see Cowan et al., 2012 for evidence that memory for high-frequency chunks of linguistic items also benefit from a similar advantage). Just as chunking-based recall tasks such as nonword repetition and serial recall provide key insights into both children's processing abilities and their current degree of real-world linguistic knowledge (Jones, 2012), SICR captures the same effects with the learning of artificial languages.

The current research tests the chunking account of learning, seeking to determine whether general memory processes can capture the acquisition of nonadjacent structures in a statistical learning paradigm and whether they are represented as chunks. Crucially, we assess whether chunking can extend beyond the mere recognition of nonadjacent relationships to items that contain generalizations of these structures. The first experiment investigates the acquisition and generalization of nonadjacent dependencies, following the methods of Frost and Monaghan (2016). The second experiment addresses the long-standing debate concerning the precise nature of the representations formed during nonadjacency learning, and tests whether such structures are represented as chunks or whether participants simply encode the relative positions of individual syllables. Together, these two experiments speak to the general issue of how nonadjacent structures are learned and generalized, the role of memory-based chunking therein, and their relation to language and cognition.

We hypothesized that nonadjacent dependency learning would boost SICR performance, suggesting that the chunking of accrued linguistic distributional information can facilitate short-term recall for sequences comprising nonadjacent dependencies in the same manner that has been observed for adjacent dependencies (e.g., Chen & Cowan, 2009; Jones & Macken, 2015). Furthermore, we hypothesized that participants would encode specific nonadjacent pairings (rather than encoding the relative positions of syllables alone or adhering to the rule structure of the stimuli). We predicted that these representations would also facilitate generalization, suggesting that statistical learning and generalization may rely upon the same memory-based mechanisms.

Experiment 1: Statistically Based Chunking of Nonadjacent Dependencies

The first experiment investigates whether general memory processes can support the learning and generalization of nonadjacent structures in an artificial language. To test this, we used the SICR task (Isbilen et al., 2020), which is a recall task where participants reproduce strings of syllables that either cohere with or violate the statistics of the presented language. Because this task entails the production of test strings, participants' responses can be transcribed and analyzed for the presence (or absence) of the specific structures from the training input. This task thereby provides a direct window into participants' representations of the language, and the potential involvement of chunking during learning. For instance, we can examine the data for two key signatures of statistical chunking behavior: whether participants recall full trigrams (i.e., full words) and the number of nonadjacent pairs recalled, with the generalization trials as the ultimate test of nonadjacent chunking. If participants recall specific trained nonadjacent pairs on the novel trials, this suggests that such pairs are represented as a single chunk in memory. We also administered a two-alternative forced-choice task (2AFC) to provide an additional measure of learning, and to make contact with the existing body of literature that tests nonadjacency learning using 2AFC (e.g., Endress & Mehler, 2009; Frost & Monaghan, 2016; Peña et al., 2002; Perruchet & Poulin-Charronnat, 2012).

We predicted that learning and generalization would be exhibited on both tests, with recall of the target items being superior to foils on SICR, and with 2AFC performance being greater than chance. Additionally, we hypothesized that participants would recall significantly more

legal trigrams (or full words) on the word learning trials, and that the statistical facilitation from legal nonadjacent dependencies would also lead to improved recall of trigrams on the generalization trials. Last, we hypothesized that participants would recall specific nonadjacent chunks from the grammatical items, suggesting that they can in fact chunk such structures.

Method

Participants—Forty-nine undergraduates (30 females, 19 males; age: $M = 19.43$, $SD = 1.30$) from Cornell University were recruited. All participants were native speakers of American English, with no known language or hearing disorders. Participation was compensated with course extra credit.

Materials—This study utilized the same artificial language as Frost and Monaghan (2016), which was adapted from Peña et al. (2002). The language comprised 9 syllables, which were used to create three nonadjacent dependencies (e.g., A–C pairings), which each featured three different middle syllables (e.g., X syllables in AXC), yielding nine distinct tri-syllabic words that were heard during training ($A_1X_1C_1$, $A_1X_2C_1$, $A_1X_3C_1$; $A_2X_1C_2$, $A_2X_2C_2$, $A_2X_3C_2$; $A_3X_1C_3$, $A_3X_2C_3$, $A_3X_3C_3$). Plosives (*be, du, ga, ki, pu, ta*) were used for the first and third syllables of each nonadjacent dependency, whereas continuants (*fo, li, ra*) were used for the middle syllables (e.g., *dufoki, duliki, duraki, gafobe, galibe, garabe, tafopu, talipu, tarapu*).[1] To ensure that the study's results were not due to the particular features of a single artificial language, four different languages with different A–C pairings were created, and were counterbalanced across participants. The words in each language version were concatenated together into a single auditory file that was presented during the training phase, with a 5-s fade in and fade out to prevent participants from using the onset and offset of the file as a cue for determining word boundaries. The transcriptions of the words for each language version can be found in Appendix A.

A further nine generalization words that were not present during training were created to test how well participants could generalize their knowledge of the trained nonadjacent dependencies. These generalization words were composed of the same nonadjacent dependencies as the input words but featured novel intervening syllables not heard during training (e.g., Z syllables in AZC). Like the input words, continuants were used for the middle syllables (*thi, ve, zo*). The transcriptions of the generalization words for each language version can be found in Appendix A.

For SICR, 26 six-syllable-long strings were created, in line with those used by Isbilen et al. (2020). Of these, nine were composed of two concatenated words (e.g., $A_1X_3C_1A_2X_1C_2$), nine were composed of two concatenated generalization words (e.g., $A_1Z_3C_1A_2Z_1C_2$), and eight were foils (to maintain equal numbers of each item type: four word-learning and four generalization foils). The foils used the same syllables as the target items but in a scrambled order, avoiding both the adjacent and nonadjacent regularities of the artificial language.

---

[1]This is in line with the language by Peña et al. (2002). Phonological similarity between syllables supports the acquisition of nonadjacent dependencies (Newport & Aslin, 2004; but see Frost et al., 2019 and Onnis et al., 2005 for evidence that this is not essential for learning).

These foils served as a baseline working memory measure, which performance on the target items was compared against to gauge learning. All SICR test items can be found in Table B1 in Appendix B.

For 2AFC, the same 18 foil words from Frost and Monaghan (2016) were used: nine part-word foils and nine generalization foils for each language version. The part-word foils spanned word boundaries (e.g., $X_1C_1A_2$, $C_2A_1X_1$), and were presented alongside the input words to test how well participants had picked up on the language's underlying structure. Similarly, the generalization foils were also part-words that spanned word boundaries, but with the X syllables replaced with novel, unheard syllables (e.g., $Z_1C_1A_2$, $C_2A_1Z_1$), which were presented at test with the target generalization words. All 2AFC foil words can be found in Table B2 in Appendix B.

All stimuli were synthesized using the Festival speech synthesizer (Black et al., 1990), with each individual trisyllabic sequence lasting approximately 700 ms. Both stimulus presentation and data collection utilized E-prime 2.0 (Schneider et al., 2002). The study was approved by Cornell University's Institutional Review Board (IRB), and participants signed a consent form prior to participation.

Procedure—First, participants were trained on the artificial language. The nine words were randomized to produce a continuous stream, and participants were instructed to listen to the language carefully and pay attention to the words it might contain. Each word was presented 100 times (with each nonadjacency pair occurring 300 times), and training lasted approximately 10.5 min. The nine words were randomized and concatenated such that there was no immediate repetition of individual AXC words.

Following exposure, participants completed two tasks: SICR and 2AFC. The order of these tasks was counterbalanced across participants. For SICR, the twenty-six strings described above were presented for recall: nine that tested word acquisition, nine that tested generalization, and eight random foil strings, to maintain equal numbers of word learning and generalization foils (four each). Participants were told that they would be assessed on how well they could reproduce the syllables present in the artificial language. They were then asked to listen to each string carefully, and to repeat the entire string out loud in the correct order as accurately as possible into a microphone as soon as it was finished playing. The order of the SICR items was randomized across individuals, and participants were not informed of any underlying structure present in the strings.

For 2AFC, participants heard eighteen pairs of words: one target word and one foil word per trial. Of these, nine pairs tested acquisition of the input words, and nine pairs tested generalization. For this task, participants were asked to listen to each word pair carefully and report which of the two items best matched the artificial language they were trained on. The order of all 2AFC trials was randomized across individuals.

Results

SICR Results—Prior to analysis, participants' verbal responses on the SICR task were transcribed by two coders who were naive to the purpose of the study and its design (see

Isbilen et al., 2020 for an in-depth guide on the transcription of SICR sequences). In line with Isbilen et al. (2020) and methods used in the nonword repetition literature (Botvinick & Bylsma, 2005), consistent syllable mispronunciations (e.g., a participant routinely says "le" for the target syllable "li") were transcribed as correct (i.e., as "li" rather than "le"), as such mispronunciations indicate differences in how participants perceive the syllables produced by the speech synthesizer. In addition, an anchoring procedure was used to align participants' productions as closely as possible to the target items, identical to what is done for many nonword repetition tasks (e.g., Dollaghan & Campbell, 1998; Ellis Weismer et al., 2000). For instance, if a target stimulus was *taragabeliki* and the participant produced "taraki," this would be transcribed as "tara------ki" (with a dash denoting each missed letter). This ensured that participants were granted credit for all of the syllables that were correctly recalled, even if they returned fewer syllables than they were presented with. In cases where there were false starts (e.g., the participant started producing a syllable, paused, then started again) and self-corrections (where a participant corrected their production of a syllable or item), the original production was ignored in favor of the second/corrected production. Nonresponses on a trial were automatically given a score of zero.

Following transcription, participants' responses on both the word learning and generalization trials were scored for accuracy using four different measures. The first measure was total accuracy (the total number of syllables that participants recalled in the correct order), which allowed us to gauge how well participants performed on each string as a whole and whether statistical learning conferred a general memory advantage. The second measure was bigram accuracy (the total number of adjacent two-syllable combinations recalled within words, out of four possible pairs: e.g., A_1X_1, X_1C_1, A_2X_2, X_2C_2 in the target sequence $A_1X_1C_1A_2X_2C_2$), which indicates how well participants encoded the adjacent bigram information within the presented structures. The third measure was trigram accuracy (the total number of trigrams or full words correctly recalled in each string, out of two possible pairs: e.g., $A_1X_1C_1$ and $A_2X_2C_2$), which revealed whether participants chunk entire words in the target word learning trials, and whether nonadjacency learning enabled better retention of novel words in the generalization trials. The final measure was nonadjacent dependency accuracy. For the target sequences, this was the number of A–C pairings that participants recalled from each string, out of two possible pairs: for example, $A_1\_C_1$ and $A_2\_C_2$. For the foils, this score was calculated based on recall accuracy for pairs of syllables in the analogous positions, that is, syllables 1 and 3, and syllables 4 and 6. This measure allowed us to determine whether participants chunked specific nonadjacent syllable combinations in the target items.

The target item scores were then compared against those of the foil items, to test statistical learning against baseline working memory. We report the results from linear mixed-effect model analyses, which used the *lmerTest* package (Kuznetsova et al., 2017) in the statistical software R, Version 4.2 (R Core Team, 2020). For the linear mixed-effects models, the models were built incrementally, participants and test items were included as random effects, and word type (target vs. foil) as a fixed effect. Language version was not included as a separate random effect in the analyses, as it was already redundantly coded in the test item variable. Each SICR measure (total, bigram, trigram, and nonadjacent dependency accuracy) was modeled separately.

On the word learning trials, when controlling for participants and test items, the fixed effect of word type on total accuracy was highly significant (model improvement over model containing only random effects, $\chi^2(1) = 43.16$, $p < .0001$), with participants correctly recalling significantly more syllables in the target items than in the foil items (difference estimate $= -1.16$, $SE = .14$, $z = -8.15$, $p < .0001$). There was also a significant effect of word type on bigram recall (model improvement over model containing only random effects, $\chi^2(1) = 36.87$, $p < .0001$; difference estimate $= -.87$, $SE = .12$, $z = -7.41$, $p < .0001$) and on trigram recall (model improvement over model containing only random effects, $\chi^2(1) = 36.73$, $p < .0001$; difference estimate $= -.42$, $SE = .06$, $z = -7.25$, $p < .0001$), with significantly higher recall accuracy of legal adjacent syllable combinations and full trigram words encountered in the input. Finally, there was a robust effect of word type on nonadjacent dependency accuracy (model improvement over model containing only random effects, $\chi^2(1) = 34.08$, $p < .0001$), with significantly more nonadjacent dependencies (syllables in the first and third serial positions and the fourth and six serial positions) being accurately recalled in the target items than the foils (which contained no nonadjacent structure; difference estimate $= -.43$, $SE = .06$, $z = -6.92$, $p < .0001$).

For the generalization items, there was a significant effect of word type on SICR total accuracy (model improvement over model containing only random effects, $\chi^2(1) = 25.77$, $p < .0001$), with participants recalling significantly more syllables in the target strings (difference estimate $= -1.00$, $SE = .17$, $z = -5.78$, $p < .0001$). The same pattern was observed for bigram accuracy (model improvement over model containing only random effects, $\chi^2(1) = 8.72$, $p = .003$; difference estimate $= -.52$, $SE = .17$, $z = -3.08$, $p = .004$) and trigram accuracy (model improvement over model containing only random effects, $\chi^2(1) = 36.73$, $p < .0001$; difference estimate $= -.42$, $SE = .06$, $z = -7.25$, $p < .0001$), with better accuracy for legal adjacent syllable combinations and full novel trigram words within the target sequences. Last, a strong effect of word type was also observed for nonadjacent dependency accuracy (model improvement over model containing only random effects, $\chi^2(1) = 21.95$, $p < .0001$), with participants recalling significantly more nonadjacent pairs within the target than foil items (difference estimate $= -.37$, $SE = .07$, $z = -5.20$, $p < .0001$).

There was no significant difference between word learning and generalization as measured by the SICR difference scores (target item score minus foil item scores), for either total accuracy, or nonadjacent dependency accuracy (both ps = .10). However, a significant difference was observed on bigram recall, $t(48) = 4.12$, $p = .0002$, $d = .59$, and trigram recall, $t(48) = 3.86$, $p = .0003$, $d = .55$. Participants recalled the bigrams and trigrams they were exposed to significantly better than the items with novel middle syllables. Mean performance on these different measures (i.e., the average proportion of syllables, bigrams, trigrams, and nonadjacent dependencies recalled across all participants for each trial type) are reported in Table 1, and the serial position curves are reported in Figure 1.

2AFC Results—As predicted, participants performed significantly above chance on both the word learning and generalization 2AFC trials (word learning: $t(48) = 18.44$, $p < .0001$, $d = 2.63$; generalization: $t(48) = 6.61$, $p < .0001$, $d = .94$). Participants' accuracy was significantly higher on the word learning than on the generalization trials, $t(48) = 5.77$, $p < .0001$, $d = .82$. The mean scores for each trial type can be found in Table 2.

Discussion

Experiment 1 provides strong evidence that participants could identify individual words in an artificial language and detect the nonadjacent dependencies it contained. Because both words and structure were defined by (adjacent and nonadjacent) transitional statistics, these data lend further support to the notion that human learners can perform computations over the distributional regularities contained in speech, even for dependencies that occur over a distance. Importantly, participants also successfully generalized statistically learned chunks of nonadjacent information and could do so in relative synchrony with learning the precise sequences that occurred, rather than requiring the progressive formation of rule-like representations after item learning had been mastered.

Importantly, the results also indicate that our ability to perform these tasks may be driven (at least in part) by statistically based chunking. On SICR, recall was significantly better for the structured strings than random foils, with participants recalling significantly more bigrams, trigrams and nonadjacent pairs for structured sequences—structures that have historically posed a challenge for chunking models. This mirrors prior work demonstrating that individuals in serial recall tasks can remember items that are interpolated by additional information, which may be seen as a kind of nonadjacent structure (Baddeley et al., 1993). For instance, when tasked with recalling strings of numbers interleaved by words (e.g., 7-wit-9-bond-6), participants can successfully ignore the words and recall the numbers, suggesting that distal information can be held in verbal working memory. This effect replicates for visual–spatial serial information (Nicholls et al., 2005), suggesting that it is a general property of memory across domains. Recall in these studies was somewhat lower for interpolated stimuli than when recall items were contiguous (with similar findings by Greene et al., 1988; Hitch, 1975; Murray, 1966), although this effect was small in Baddeley et al. (1993) and Nicholls et al. (2005). The current study moves beyond these results, investigating memory for nonadjacent information following a training phase on an artificial language, to measure learning-induced changes to recall. Although previous studies have shown that participants can suppress interleaved information, here we find that individuals can recall adjacent and nonadjacent information simultaneously and with comparable accuracy, facilitated by statistical learning.

The enhanced trigram recall on the target word learning trials suggests that participants had chunked the syllables into wholistic word-like representations during training. Higher trigram recall on the target generalization items implies that the chunking of nonadjacent dependencies facilitated recall of the new intervening items by reducing memory load. These findings with nonadjacent patterns parallel prior research underscoring the contribution of chunking to representing learned adjacent items in memory in serial recall (Chen & Cowan, 2009) and nonword repetition (Jones et al., 2014), and how long-term statistical knowledge interacts with these abilities (Cowan et al., 2012; Jones, 2012; Jones & Macken, 2015). Just as prior studies report memory advantages for learned chunks of adjacent information, here we extend these results to the statistical learning of nonlocal structures, demonstrating how the statistical learning of such structures are relevant for broader theories of cognition and memory.

Additionally, participants also recalled significantly more trained nonadjacent dependencies —specific A–C combinations—in the target items than the foils (which did not contain this structure). This was true for both the word learning and generalization sequences, suggesting that participants formed chunked representations of these dependencies, which they could use flexibly in novel instances. Participants' knowledge of the nonadjacent dependencies therefore appears to facilitate their ability to recall information on the generalization trials, whereas the word learning trials demonstrate evidence of specific item learning. To our knowledge, the present study is the first to demonstrate that long-term distributional knowledge facilitates memory for nonadjacent items in the same manner that has been observed for adjacent items.

Using two assessments of learning (SICR and 2AFC), we replicated Frost and Monaghan's (2016) finding that adults can identify words and word-internal dependency structures together during learning, from statistical information alone (without the need for additional cues, e.g., Fló, 2021; Peña et al., 2002), indicating that these tasks may be underpinned by similar statistical learning and memory processes (see Frost & Monaghan, 2016 for further discussion). Our results thus provide further evidence for the notion that learning and generalization may simply be different outcomes of the same statistical learning processes (Aslin & Newport, 2012) rather than generalization requiring separate rule-like computations, suggesting a more unified framework for nonadjacent dependency learning and language acquisition at large. However, some outstanding questions about how nonadjacent information is represented in memory remain, including whether such information is represented as chunks or merely encoded positionally.

Experiment 2: Chunked Representations of Nonadjacent Dependencies

Experiment 1 provides initial support for the chunking of whole words, and the specific nonadjacent syllables within them. However, the results might be explained by an alternative possibility: that participants encoded the relative positions of the syllables rather than the nonadjacent dependencies as chunks (Endress & Mehler, 2009). Potential evidence against the chunking hypothesis and for the positional information hypothesis comes from participants' inability to distinguish trained nonadjacent dependencies (e.g., A_1XC_1) from items that violate the language's chunk information while preserving its positional information, by replacing the final syllable of one trained dependency with the final syllable of another (e.g., A_1XC_2). These items, first introduced as "class words" (Endress & Bonatti, 2007) and later as "phantom words" (Endress & Mehler, 2009) reportedly led participants to have false memories of hearing these words during training, thus suggesting that positional information—and not chunk information—is the outcome of nonadjacent dependency learning. However, others have since shown that participants exhibit a general preference for trained words over phantom words—consistent with the predictions of chunking-based computational models (Perruchet & Poulin-Charronnat, 2012). However, what participants specifically represent—trigrams, nonadjacent dependencies, or both—remains an open question.

Given that most prior investigations into this phenomenon have utilized 2AFC, we sought to revisit the phantom word effect using SICR. As SICR affords more specific insights

into learners' representations, we reasoned that it may grant clearer insights into whether participants acquire chunk information or only positional information. Unlike previous work on this topic, we tested both acquisition and generalization rather than acquisition alone. We hypothesized that participants would differentiate between trained and phantom items, showing learning of specific chunks rather than solely positional information. However, we hypothesized that this would only be on the SICR task, due to the increased specificity that the recall data provides about participants' representations relative to 2AFC.

Method

Participants—We collected data from 75 participants (49 females, 25 males, one nonbinary; age $M = 20.65$, $SD = 3.07$). Due to the COVID-19 pandemic, this experiment was conducted online. We recruited from both the Cornell University undergraduate population ($N = 50$) and from the Prolific participant recruitment platform ($N = 25$). Participation from the Prolific participant pool was limited to university students who were native speakers of American English, to maintain comparability between the two samples. There were no significant differences in performance between the two samples on either SICR or 2AFC ($p = .24$ or greater). Therefore, the data from both samples were combined and analyzed together.

This preregistered sample size was determined by a power analysis based on the results of a pilot experiment run in-lab, wherein we observed a SICR effect size of approximately $d = .41$. Due to the online format of the current study, we anticipated that the observed effect sizes might be slightly smaller than the pilot study that was conducted in-person prior to lab closures (e.g., due to potential delays between stimulus presentation and when participants are cued to start repeating back stimuli because of differences in Internet connectivity, differences in headphone types across participants, slight differences in the volume at which participants listen to stimuli). We therefore conducted a power analysis based on a reduced effect size of $d = .21$ (half of the effect size observed in the pilot study). All participants were native speakers of American English, with no known history of language or auditory disorders. Participation was compensated with course extra credit or monetary payment.

Materials—The same four artificial languages as Experiment 1 were used, featuring nine AXC words that were heard during training. In addition, the same 18 SICR and 18 2AFC target items as Experiment 1 were used at test (nine that tested word learning and nine that tested generalization in each task). For the foils, eighteen phantom words were created. Phantom words were constructed by taking the first syllable of one nonadjacent dependency and pairing it with the final syllable of a different nonadjacent dependency (e.g., $A_1X_1C_2$), to preserve the items' positional information but disrupt their chunk information (i.e., A1 and C_2 occur as the first and last syllable in a trisyllabic sequence, but never occurred together within the same trisyllabic word during training). The same method was used to create four SICR phantom word learning trials ($A_1X_3C_2A_2X_1C_1$) and four SICR phantom generalization trials ($A_1Z_3C_2A_2Z_1C_1$), yielding eight SICR phantom word trials in total. The bigram information in the foils was carefully balanced, to make sure that no single bigram appeared in the phantom word strings more than once, and all phantom A–C pairings

occurred an approximately equal number of times. The phantom word items for both tasks can be found in Tables C1 and C2 in Appendix C.

As in Experiment 1, all new stimuli were generated using the Festival speech synthesizer (Black et al., 1990), using the same voice as the items in the first experiment, with each tri-syllabic string lasting approximately 700 ms. Both stimulus presentation and 2AFC data collection utilized Qualtrics survey software. Participants' spoken responses on the SICR task were recorded using the Zoom conferencing software, in a completely anonymized meeting session (participants logged in with their randomized participant numbers and with no video, to ensure that the data was completely de-identified), as was approved by Cornell University's IRB. Participants signed a consent form prior to participation.

Procedure—Identical to Experiment 1, participants were first trained on the artificial language for approximately 10.5 min. During this time, they were asked to listen carefully to the language and pay attention to any words it might contain. Each word was presented 100 times (and so each nonadjacent dependency was presented 300 times) throughout the course of training.

Following exposure, word learning and generalization were measured using both SICR and 2AFC. The order of these two tests was counterbalanced across participants. In SICR, participants heard strings of syllables over headphones, and were asked to repeat the entire string out loud to the best of their ability. Participants were not informed of the strings' underlying structure. For 2AFC, participants heard stimulus pairs consisting of words and phantom words. On the word learning trials, input words were always paired with phantom input words. On the generalization trials, generalization words were always paired with phantom generalization words. Participants were instructed to indicate which of the two words best matched the artificial language to which they were exposed.

Results

SICR Results—As in Experiment 1, two coders who were blind to the purpose of the study and its design transcribed the SICR data, using the same procedures described in the Results section of Experiment 1. Participants' productions were then scored for total syllable, bigram, trigram, and nonadjacent dependency accuracy, and learning was measured by comparing responses on the target items to those on the phantom word items. Word learning and generalization responses were modeled separately using linear mixed effects models, with participants and test item as random effects, and word type (target vs. phantom word) as a fixed effect. As in Experiment 1, language version was not included in the models as a separate random effect, as it was already redundantly coded within the test item variable.

When considering the total recall accuracy on the word learning trials (i.e., the total number of syllables recalled), the fixed effect of word type was not significant (model improvement over model containing only random effects, $\chi^2(1) = 2.60$, $p = .11$), with no reliable difference between the number of syllables recalled for target and phantom word strings (difference estimate $= -.23$, $SE = .15$, $z = -1.61$, $p = .11$). Similarly, there was no significant effect of word type on bigram recall (model improvement over model containing

only random effects, $\chi^2(1) = 2.42$, $p = .12$), with performance on both target and phantom strings being approximately equal (difference estimate $= -.22$, $SE = .14$, $z = -1.55$, $p = .13$). However, there was a significant effect of trigram accuracy (model improvement over model containing only random effects, $\chi^2(1) = 4.35$, $p = .037$). Participants recalled significantly more legal trigrams than phantom trigrams (difference estimate $= -.16$, $SE = .08$, $z = -2.11$, $p = .04$). Similarly, nonadjacent dependency accuracy was significantly higher for the target items (model improvement over model containing only random effects, $\chi^2(1) = 7.53$, $p = .006$), with participants recalling more nonadjacent dependencies that they were exposed to during training than phantom dependencies (difference estimate $= -.18$, $SE = .06$, $z = -2.82$, $p = .007$).

For SICR generalization, the data reveal the same pattern of results as those observed for the word learning trials. Similarly, there was no significant effect of item type on bigram accuracy (model improvement over model containing only random effects, $\chi^2(1) = 1.25$, $p = .26$; difference estimate $= -.13$, $SE = .12$, $z = -1.11$, $p = .27$). However, for trigram recall, word type was significant (model improvement over model containing only random effects, $\chi^2(1) = 4.35$, $p = .037$), with participants recalling significantly more trained trigrams over phantom trigrams (difference estimate $= -.16$, $SE = .08$, $z = -2.11$, $p = .041$). Nonadjacent-dependency recall was also significantly impacted by word type (model improvement over model containing only random effects, $\chi^2(1) = 5.00$, $p = .026$), with participants recalling significantly more nonadjacent dependencies for the target items than in the phantom word items (difference estimate $= -.13$, $SE = .06$, $z = -2.62$, $p = .03$).

Performance was significantly higher on the word learning trials than on the generalization trials for all SICR measures (total accuracy: $t(74) = 2.63$, $p = .01$, $d = .30$; bigram accuracy: $t(74) = 3.81$, $p = .0003$, $d = .44$; trigram accuracy: $t(74) = 3.63$, $p = .0005$, $d = .42$; nonadjacent dependency accuracy: $t(74) = 2.04$, $p = .05$, $d = .24$). Mean performance on all SICR measures (e.g., the average proportion of syllables, trigrams or nonadjacent dependencies recalled across all participants for each trial type) are reported in Table 3, and the serial position curves are reported in Figure 2.

2AFC Results—Contrary to our preregistered predictions, 2AFC word identification performance was significantly above chance, with participants preferring words over phantom words, $t(74) = 5.87$, $p < .0001$, $d = .68$. Generalization performance was also significantly above chance, $t(74) = 1.67$, $p = .05$, $d = .19$, with participants correctly selecting novel but structurally consistent words constructed of target nonadjacent dependencies over phantom dependencies. There was a significant difference between 2AFC word learning and generalization performance, $t(74) = 3.03$, $p = .003$, $d = .35$, with participants performing significantly better on the word learning than the generalization trials. The mean accuracy of each 2AFC measure is reported in Table 4.

Discussion

In Experiment 2, we expanded on the results of Experiment 1 by performing a closer examination of the representations that learners form during statistical nonadjacent dependency learning. In doing so, we revisited the positional hypothesis proposed by

Endress and Mehler (2009), but with two key differences from previous studies. First, we tested generalization in addition to acquisition, to determine whether the effect reported for phantom input words would extend to generalization. Second, we used SICR to gain more detailed insights into participants' representations for the newly acquired words/structures, to disentangle whether these comprise chunks or merely positional information.

Our results reveal that participants may become sensitive to multiple kinds of regularities in nonadjacency tasks, including both adjacent and nonadjacent information. However, it also appears that they do encode specific nonadjacent chunks above and beyond the positions of syllables alone. For SICR, contrary to our predictions, no difference was found between recall of the target versus phantom words in terms of the total number of syllables recalled or the number of bigrams recalled. This finding makes sense when considering the overall statistical structure of the target and phantom items: in both cases, the adjacent bigram information was identical. The only differences between the two lay in the trigram and nonadjacency statistics. We observed a robust difference in both the number of legal trigrams and legal nonadjacent dependencies recalled, both on the word learning and generalization trials. Although the distinctions between the target and phantom word items were very subtle in terms of their statistical structure, participants nonetheless recalled significantly more trigrams and nonadjacent dependencies that followed the artificial language's chunk information. These findings dovetail with experimental data on visual statistical learning from Slone and Johnson (2015), demonstrating that participants can distinguish trained triplets from statistically matched illusory triplets, and thus represent chunks rather than statistics. Comparable results have also been reported for linguistic statistical learning (Perruchet & Poulin-Charronnat, 2012; Wang et al., 2019). However, although these previous studies have demonstrated a general preference for trained over phantom items, here we elucidate the specific representations that learners accrue.

The stronger facilitation from legal nonlocal dependencies has several implications for the kind of information that participants glean from learning. Work from a recent study of online visual statistical learning shows that there are strong individual differences in the kinds of dependencies—local versus nonlocal—that participants rely on (Siegelman et al., 2019), with some individuals preferring one over the other, whereas some attend to both. Overall, adjacent information appears to be easier for participants to process and learn (Trotter et al., 2020), with participants potentially favoring adjacent over nonadjacent dependencies when such information is present (Gómez, 2002). Indeed, Gómez (2002) found that individuals could only learn nonlocal over local information when there was ample variability of the middle items in the input—even with the inclusion of additional pause and lexical cues to the nonadjacent structure. The languages in the present experiment possessed no additional cues and very few middle items: only three as opposed to the twenty-four middle items required in Gómez (2002) for participants to endorse grammatical over ungrammatical nonadjacent sequences above chance in a grammaticality judgment task. Here, we contribute further evidence that individuals can in fact learn and represent adjacent transitional probability information and nonadjacent information simultaneously, supplementing the results of prior studies (Romberg & Saffran, 2013; Vuong et al., 2016). Complementary findings are also observed in studies of children's nonword repetition using stimuli derived from natural language statistics: Through exposure to a language, individuals

pick up on lexical chunks (in this case, nonadjacent frames) and sublexical chunks (e.g., the bigram information within those frames), leading to enhanced recall of strings that follow these lexical and sublexical statistics (Jones, 2016). These findings also illustrate how the behaviors observed in the current article tap into real-world psychological phenomena.

Contrary to the results of Endress and Mehler (2009) and in line with those of Perruchet and Poulin-Charronnat (2012), our 2AFC results show a significant difference between endorsement of the words over phantom words on the word identification trials. Further, we extend these results by observing a comparable effect on the generalization trials. These trials in particular discount the idea that individuals encode rule-like representations regarding syllable position—participants show better endorsement of target over phantom items even though both follow the purported rule structure (e.g., A precedes C). Rather, individuals appear to encode specific A–C combinations, suggesting the acquisition of concrete items over abstract rules. These results thus lend important insights into the nature of exemplar-based learning and generalization, and how the two unfold over time: individuals represent learned items with enough flexibility to generalize over exemplars relatively early during the learning process.

General Discussion

Successful learning necessitates more than the encoding of specific items or events in the environment—it requires generalizing to novel instances. The current article tested the question: can general-purpose statistical learning and memory processes account for the acquisition and generalization of nonlocal dependencies, a common challenge to many memory and exemplar-based learning models? Our results provide strong evidence for the statistically based chunking of nonadjacent structure that is not reducible to positional encoding and does not require rule learning. The results also suggest that participants represent nonadjacent information as input-specific chunks that can scaffold structural generalization (Lieven, 2016).

In line with statistical learning-based theories (e.g., Aslin & Newport, 2012), our results suggest that structure learning and generalization may be more computationally unified in adults than previously assumed (Endress & Bonatti, 2016). Rather than these two abilities requiring distinct statistical and rule-like computations, they can instead rely on similar statistical learning and memory mechanisms (e.g., Frost & Monaghan, 2016; Perruchet et al., 2004). Furthermore, although some theories posit that statistical information is insufficient for the acquisition of nonadjacent structures from speech, let alone generalization (Endress & Mehler, 2009; Endress et al., 2005), we show that nonadjacent dependencies can be both acquired and generalized without the recruitment of additional cues, replicating the results of previous studies (Frost & Monaghan, 2016). Although the recruitment of additional cues can facilitate the acquisition of nonlocal dependency structures (e.g., de Diego-Balauger et al., 2007, 2015; Fló, 2021; Newport & Aslin, 2004; Rodríguez-Fornells et al., 2009; Van den Bos et al., 2012), they are not a strict requirement for learning (Frost et al., 2019; Onnis et al., 2004).

Our results further elucidate how individuals move from exemplar-based learning to forming broader generalizations—a key area of inquiry in psychology. Rather than requiring the gradual formation of abstract rules, learners appear to chunk specific exemplars from the input based on adjacent and nonadjacent statistical regularities (e.g., *I__them*), which serve as a launchpad for generalizing beyond what was encountered (e.g., *I saw them, I like them, I want to eat them*). These results parallel usage-based frameworks of language acquisition (e.g., Lieven, 2016; Tomasello, 2003), which view productivity as arising from the interplay of encoding input-specific constructions and abstracting over them to create novel variations. For example, learners appear to extract and store lexical frames (Lieven et al., 2003), which are specific multiword constructions that frequently occur in an input (e.g., *I want __*). Productivity occurs when learners insert a novel word or multiword chunk into the empty slot of the frame (e.g., *I want this, I want to go home*), enabling learners to generalize over statistically learned chunks.

A chunking-based computational model that discovers lexical frames may provide a window into how chunking could operate in the learning and generalization that took place in our experiments. This lexical frame discovery model involves a minor, principled extension to an earlier chunk-based learner model (CBL; McCauley & Christiansen, 2019a), which aimed to simulate children's language comprehension and production under real-time memory constraints. CBL was exposed to corpora of child-directed speech—one word at a time— using backward transitional probabilities between words (which learners are sensitive to: e.g., Pelucchi et al., 2009; Perruchet & Desaulty, 2008; Saffran, 2001, 2002) to decide whether to group words together as a chunk or not. In this way, the model processes the input incrementally, while building up an inventory of chunks that consist of one or more words. Through a simple generalization process, multiword chunks can then be used to facilitate further processing: previous encountered chunks are automatically grouped together independently of transitional probability information. As a model of early language acquisition, CBL was able to simulate the kind of shallow parsing that likely plays a role in children's language comprehension and the use of distributional regularities in their production of utterances. The model showed strong performance across a typologically diverse range of languages (McCauley & Christiansen, 2019a) while also capturing psycholinguistic data from both children (McCauley & Christiansen, 2014) and adults (Grimm et al., 2017).

This lexical frame version of CBL (CBL+LF; McCauley & Christiansen, 2019b) incorporated a slight change to the generalization process: when the model has discovered five or more multiword chunks of the same size and which differ only by a single word (in the same position), it creates a lexical frame with an empty slot. For example, if the model learns the chunks *on our own, on your own, on their own, on his own, on its own*, it automatically generalizes over them to create the lexical frame *on__own*.[2] These lexical frames are stored in the model's chunk inventory (or long-term memory), where they can

---

[2] The CBL+LF model thus answers the call by Kol et al. (2014) for the kind of psychologically plausible, yet computationally rigorous, approximation of the Traceback method proposed by Lieven et al. (2003) to capture children's item-based language learning. The threshold of 5+ for creating a lexical frame was chosen as a more conservative constraint than the 4+ used by Cameron-Faulkner et al. (2003) in their hand-coded analysis of child-directed speech.

combine with other words and chunks to produce novel utterances not encountered in the input (e.g., *on my own*, *on her own*). The model thus demonstrates how the combination of statistical learning and chunking mechanisms can capture the generalization of nonadjacent structures. These simulations, along with the data presented here, suggest that chunks do not only comprise contiguous units, but can also incorporate nonadjacent lexical frames wherein other chunks can be placed, thereby extending the results of prior memory models.

Importantly, these results show that chunk formation and statistical dependency learning are part and parcel of the same learning process. In Experiment 1, participants appear to form chunks of information based on the different statistics present in the input (Perruchet & Poulin-Charronnat, 2012; Slone & Johnson, 2015, 2018; Wang et al., 2019), encoding specific trigrams from the input as well as nonadjacent dependencies. Experiment 2 provided further evidence of this ability, by illustrating how participants encode nonadjacent chunks beyond positional information, though they still encode adjacent information as well (exemplified by the fact that participants recall the bigrams equally well in the target and phantom items). It may thus be the case that theories of statistical learning need not rule out the acquisition of transitional probabilities in favor of chunk information, or vice-versa —rather, learners appear to utilize both. Indeed, computational models that involve both statistical computation and chunk formation provide a stronger fit to statistical learning data than those that exclusively rely on transitional probability calculation (French et al., 2011; McCauley & Christiansen, 2019a, 2019b; Perruchet & Vinter, 1998), and is consistent with theories that view statistical learning as a suite of domain-general computations (Frost et al., 2015, 2019). Although our data cannot determine whether chunk formation and statistical computation occur in parallel (McCauley & Christiansen, 2019a, 2019b), or if statistical sensitivity manifests due to chunking (Perruchet & Vinter, 1998; Perruchet & Pacton, 2006; Thiessen & Pavlik, 2013), they do suggest that both are required for learning and generalization.

Our results also contribute further insights to the memory literature, and particularly to studies employing serial recall. Individuals who have picked up on the statistical regularities of artificial languages show better recall of grammatical items, when controlling for baseline phonological working memory (Conway et al., 2010; Isbilen et al., 2020; Kidd et al., 2020). Similarly, memory for sequences of high frequency words from natural language is superior to memory for strings of low frequency words (Hulme et al., 1997), and long-term lexical and phonological knowledge facilitates recall, when test items are manipulated to leverage distributional regularities from an artificial language that participants were exposed to (Majerus et al., 2004). Other studies have shown that when individuals are trained to associate pairs of words, these pairs are later treated as a single chunked unit (Cowan, Chen, & Rouder, 2004), and classic memory studies show that word predictability and frequency facilitate recall (Baddeley, Conrad, & Hull, 1965). Although prior observations have typically been limited to facilitation from adjacent statistical information, we extend these findings here by showing comparable boosts to memory performance from the statistical learning of nonadjacent information.

The question of how nonadjacent information may be stored in memory is a topic of some speculation. For example, in the visual domain, some studies suggest that individuals utilize

such structural dependencies to simplify their mental representation of stimuli to allow their retention in memory. This is thought to take different forms, with individuals encoding both detailed information about specific items and the overall summary of a scene (Brady & Tenenbaum, 2013; Hollingworth & Henderson, 2003; Oliva, 2005), or by regularizing the features of a scene to facilitate compressibility and reduce short-term memory (STM) load—though such compression may also cause memory errors by oversimplifying the data (Lazartigues et al., 2021). Yet other studies have challenged the notion of chunking as a form of data compression that frees up working memory (Norris et al., 2020), and instead suggest that chunking may be achieved by redintegration. In this account, chunked representations only reside in long-term memory, enabling individuals to rebuild whole representations from degraded traces in STM (but, see Brady et al., 2009 and Thalmann et al., 2019 for evidence of compression in memory). Although the current article was not designed to disentangle the compression and redintegration accounts, our data do suggest that nonadjacent statistical information appears to facilitate memory in a similar fashion as adjacent information: by allowing the cognitive system to build larger units of representation, and thereby decreasing the number of items that need to be held in working memory. This is consistent with chunking models of serial recall (e.g., Cowan et al., 2012), which show that working memory limitations interact with long term memory. Although this and other models have primarily focused on items linked by adjacent probabilities, their results may extend to items comprising nonadjacent regularities as well.

Additionally, acquisition and generalization appear to occur in parallel, rather than requiring mastery of the language before evidence of generalization can be observed, as has been previously suggested. However, although these two abilities appear to emerge around the same time at test, we acknowledge the limitations of the current study in providing online data that tracks the time course of learning during training, or the specific mechanisms involved therein. Just as decades of 2AFC results are taken to be indicative of the calculation of transitional probabilities during statistical learning, we predict that the evidence of chunk formation on SICR may similarly indicate the involvement of chunking during learning, and the apparent concurrence of learning and generalization.

Furthermore, our data do not speak to how word learning and generalization proceed in infants, nor its developmental trajectory (Gómez & Maye, 2005). Evidence for how these abilities unfold in infants is currently mixed. Indeed, it has previously been suggested that generalization may only appear later in development—and only then with the incorporation of additional acoustic cues (Marchetto & Bonatti, 2013). Yet the opposite has been reported for the acquisition of musical sequences (Dawson & Gerken, 2009), with 4-month-old infants successfully generalizing tone and chord combinations that follow a regular pattern, but not 7-month-old infants. By contrast, Frost et al. (2020) show that 17-month-old children both segment and generalize structure after a brief period of exposure to an artificial speech stream on the basis of statistical cues alone. Similar results have also been observed for visual statistical learning (Saffran et al., 2007). Although these results make it difficult to untangle the precise developmental timeline of generalization, collectively, they do suggest that it occurs for both linguistic and nonlinguistic stimuli. As this ability applies across domains, it thus may be underpinned by general cognitive rather than language-specific mechanisms.

The processes involved in learning and generalization have long been debated. Here, we suggest that the process characterized as statistical learning may involve a whole host of domain-general computations working in parallel (Frost et al., 2015, 2019), among which chunking plays a central role. This view differs somewhat from other accounts that propose multiple task-specific mechanisms (the "more than one mechanism" (MOM) hypothesis; Endress & Bonatti, 2007, 2016), where statistical computations calculate transitional probabilities among adjacent and nonadjacent information in speech, whereas a secondary mechanism extracts rules. Instead, we suggest that statistically facilitated chunking works in tandem with other domain-general processes to enable the learning and generalization of structure in memory, language, and other aspects of cognition.

Context of the Research

Although chunking models are powerful in capturing the learning of temporally and spatially contiguous information across domains, how such memory mechanisms might apply to remote dependencies has remained a relative mystery. Research into this area provides fertile ground for investigating the nature of exemplar-based learning and how individuals form generalizations over items—the representational foundations of vocabulary and grammar in the psychology of language and in cognitive science at large. Prior evidence shows that SICR is a highly sensitive tool for investigating learning and representation of adjacent dependencies. The current study was motivated by the question of whether SICR could be expanded to nonlocal dependencies, which would allow for a broader notion of chunking. Our results thus unlock a trove of possibilities for studying learning and generalization in a range of participants and tasks. Fruitful future directions may include investigating how representations change with age (e.g., are children more flexible in their acquisition or generalization of structures than adults?), how children with language disorders perform on tasks involving the chunking of adjacent and nonadjacent structures, whether skill in one statistical learning task correlates with skill in another, whether the learning of artificial dependencies correlates with the kinds of information individuals can learn in the real world, and how statistical learning relates to other aspects of cognition, such as auditory and visual perception, and memory and attention systems. Such avenues may in turn enable us to bridge statistically based chunking in language to a host of broad phenomena in cognition.

Acknowledgments

Appendix A: Input and Generalization Words for Experiments 1 and 2

Language 1	Language 2	Language 3	Language 4
Input words			
Dufoki	Befoki	Dufoga	Dufoki
Duliki	Beliki	Duliga	Duliki
Duraki	Beraki	Duraga	Duraki
Gafobe	Dufopu	Kifobe	Pufobe
Galibe	Dulipu	Kilibe	Pulibe
Garabe	Durapu	Kirabe	Purabe
Tafopu	Tafoga	Pufota	Tafoga
Talipu	Taliga	Pulita	Taliga
Tarapu	Taraga	Purata	Taraga
Generalization words			
Duthiki	Bethiki	Duthiga	Duthiki
Duveki	Beveki	Duvega	Duveki
Duzoki	Bezoki	Duzoga	Duzoki
Gathibe	Duthipu	Kithibe	Puthibe
Gavebe	Duvepu	Kivebe	Puvebe
Gazobe	Duzopu	Kizobe	Puzobe
Tathipu	Tathiga	Puthita	Tathiga
Tavepu	Tavega	Puveta	Tavega
Tazopu	Tazoga	Puzota	Tazoga

Appendix B: Test Items for Experiment 1

Table B1

SICR Items for Experiment 1

Input word (W) or Generalization (G) item	Target (T) or foil (F)	Language 1	Language 2	Language 3	Language 4
W	T	Dulikitafopu	Duliputafoga	Pulitakifobe	Pulibedufoki
W	T	Durakigafobe	Durapubefoki	Puratadufoga	Purabetafoga
W	T	Talipugarabe	Taligaberaki	Kilibeduraga	Dulikitaraga
W	T	Tarapugalibe	Taragabeliki	Kirabeduliga	Durakitaliga
W	T	Tafopuduliki	Tafogadulipu	Kifobepulita	Dufokipulibe
W	T	Galibeduraki	Belikidurapu	Duligapurata	Taligapurabe
W	T	Garabedufoki	Berakidufopu	Duragapufota	Taragapufobe
W	T	Gafobetalipu	Befokitaliga	Dufogakilibe	Tafogaduliki
W	F	Gabepulirata	Bekigalirata	Dugabeliraki	Tagakiliradu
W	F	Litapukidofu	Litagapufodu	Likibetafopu	Lidukibefopu
W	F	Foraduputaki	Foradugatapu	Forapubekita	Forapukidube
W	F	Kiberaligadu	Pukiralibedu	Tagaralidupu	Begaralitapu
W	F	Pubelifogata	Gakilifobeta	Begalifoduki	Kigalifotadu

Input word (W) or Generalization (G) item	Target (T) or foil (F)	Language 1	Language 2	Language 3	Language 4
G	T	Duvekitathipu	Duveputathiga	Puvetakithibe	Puvebeduthiki
G	T	Duzokigavebe	Duzopubeveki	Puzotaduvega	Puzobetavega
G	T	Duthikigazobe	Duthipubezoki	Puthitaduzoga	Puthibetazoga
G	T	Tavepugathibe	Tavegabethiki	Kivebeduthiga	Duvekitathiga
G	T	Tazopuduthiki	Tazogaduthipu	Kizobeputhita	Duzokiputhibe
G	T	Tathipuduveki	Tathigaduvepu	Kithibepuveta	duthikipuvebe
G	T	Gavebetazopu	Bevekitazoga	Duvegakizobe	Tavegaduzoki
G	T	Gazobetavepu	Bezokitavega	Duzogakivebe	Tazogaduveki
G	T	Gathibeduzoki	Bethikiduzopu	Duthigapuzota	Tathigapuzobe
G	F	Kipuvethitadu	Pugavethitadu	Tabevethikipu	Bekivethidupu
G	F	Bekithizoduga	Kiputhizodube	Gatathizopudu	Gabethizoputa
G	F	Dubezovegaki	Dukizovebepu	Pugazoveduta	Pugazovetabe
G	F	Vetabegapuzo	Vetakibegazo	Vekigadubezo	Vedugatakizo

Table B2

2AFC Foil Items for Experiment 1

Input word (W) or Generalization (G) foil	Language 1	Language 2	Language 3	Language 4
W	Bedufo	Fokibe	Bepura	Bedura
W	Fobega	Gadura	Fogadu	Betafo
W	Kigafo	Kidufo	Gapufo	Fogata
W	Kitara	Ligabe	Libedu	Gapufo
W	Libedu	Likidu	Ligapu	Kipura
W	Likita	Liputa	Litaki	Libedu
W	Lipuga	Pubefo	Rabepu	Ligapu
W	Pudura	Putara	Tadufo	Likita
W	Rapudu	Ragadu	Takira	Rakipu
G	Begave	Fothibe	Bekizo	Beputhi
G	Fothiga	Gatazo	Fothidu	Fothita
G	Kiduthi	Kibeve	Gaduve	Gatave
G	Liveta	Liveta	Liveki	Kiduzo
G	Putazo	Puduthi	Razopu	Livedu
G	Razodu	Razodu	Taputhi	Razopu
G	Thiputa	Thigata	Thibeki	Thikidu
G	Vekidu	Vepudu	Vetapu	Vebepu
G	Zobega	Zokibe	Zogadu	Zogata

Appendix C: Test Items for Experiment 2

Table C1

SICR Items for Experiment 2

Input word or Generalization item	Target or foil	Language 1	Language 2	Language 3	Language 4
W	T	Talipugarabe	Taligaberaki	Kilibeduraga	Dulikitaraga
W	T	Gafobetalipu	Befokitaliga	Dufogakilibe	Tafogaduliki
W	T	Tafopuduliki	Tafogadulipu	Kifobepulita	Dufokipulibe
W	T	Garabedufoki	Berakidufopu	Duragapufota	Taragapufobe
W	T	Tarapugalibe	Taragabeliki	Kirabeduliga	Durakitaliga
W	T	Galibeduraki	Belikidurapu	Duligapurata	Taligapurabe
W	T	Dulikitafopu	Duliputafoga	Pulitakifobe	Pulibedufoki
W	T	Durakigafobe	Durapubefoki	Puratadufoga	Purabetafoga
W	F	Talibegarapu	Talikiberaga	Kiligadurabe	Duligataraki
W	F	Galikitafobe	Beliputafoki	Dulitakifoga	Talibedufoga
W	F	Dulipugafoki	Duligabefopu	Pulibedufota	Pulikitafobe
W	F	Dufoputaraki	Dufogatarapu	Pufobekirata	Pufokidurabe
G	T	Duzokigavebe	Duzopubeveki	Puzotaduvega	Puzobetavega
G	T	Gafibeduzoki	Befikiduzopu	Dufigapuzota	Tafigapuzobe
G	T	Tazopudufiki	Tazogadufipu	Kizobepufita	Duzokipufibe
G	T	Gazobetavepu	Bezokitavega	Duzogakivebe	Tazogaduveki
G	T	Duvekitafipu	Duveputafiga	Puvetakifibe	Puvebedufiki
G	T	Gavebetazopu	Bevekitazoga	Duvegakizobe	Tavegaduzoki
G	T	Tafipuduveki	Tafigaduvepu	Kifibepuveta	Dufikipuvebe
G	T	Dufikigazobe	Dufipubezoki	Pufitaduzoga	Pufibetazoga
G	F	Tazokiduvepu	Tazopuduvega	Kizotapuvebe	Duzobepuveki
G	F	Gazopudufibe	Bezogadufiki	Duzobepufiga	Tazokipufiga
G	F	Tavebegafipu	Tavekibefiga	Kivegadufibe	Duvegatafiki
G	F	Duzobetafiki	Duzokitafipu	Puzogakifita	Puzogadufibe

Table C2

2AFC Phantom Word Foils Items for Experiment 2

Input word or Generalization foil	Language 1	Language 2	Language 3	Language 4
W	Dulipu	Duliga	Pulibe	Puliki
W	Durabe	Duraki	Puraga	Puraga
W	Dufopu	Dufoga	Pufobe	Pufoki
W	Talibe	Taliki	Kiliga	Duliga
W	Taraki	Tarapu	Kirata	Durabe
W	Tafobe	Tafoki	Kifoga	Dufoga
W	Galiki	Belipu	Dulita	Talibe
W	Garapu	Beraga	Durabe	Taraki
W	Gafoki	Befopu	Dufota	Tafobe

Input word or Generalization foil	Language 1	Language 2	Language 3	Language 4
G	Duvepu	Duvega	Puvebe	Puveki
G	Duzobe	Duzoki	Puzoga	Puzoga
G	Duthibe	Duthiki	Puthiga	Puthiga
G	Tavebe	Taveki	Kivega	Duvega
G	Tazoki	Tazopu	Kizota	Duzobe
G	Tathiki	Tathipu	Kithita	Duthibe
G	Gaveki	Bevepu	Duveta	Tavebe
G	Gazopu	Bezoga	Duzobe	Tazoki
G	Gathipu	Bethiga	Duthibe	Tathiki

References

Aslin RN, & Newport EL (2012). Statistical learning: From acquiring specific items to forming general rules. Current Directions in Psychological Science, 21(3), 170–176. 10.1177/0963721412436806 [PubMed: 24000273]

Baddeley AD, Conrad R, & Hull AJ (1965). Predictability and immediate memory for consonant sequences. The Quarterly Journal of Experimental Psychology, 17(2), 175–177. 10.1080/17470216508416429

Baddeley A, Papagno C, & Andrade J (1993). The sandwich effect: The role of attentional factors in serial recall. Journal of Experimental Psychology: Learning, Memory, and Cognition, 19, 862–870. 10.1037/0278-7393.19.4.862

Bauer PJ, & Dow GA (1994). Episodic memory in 16-and 20-month-old children: Specifics are generalized but not forgotten. Developmental Psychology, 30(3), 403–417. 10.1037/0012-1649.30.3.403

Black AW, Taylor P, & Caley R (1990). The Festival Speech Synthesis System. Centre for Speech Technology Research (CSTR), University of Edinburgh.

Bonatti LL, Peña M, Nespor M, & Mehler J (2006). How to hit Scylla without avoiding Charybdis: Comment on Perruchet, Tyler, Galland, and Peereman (2004). Journal of Experimental Psychology: General, 135(2), 314–321. 10.1037/0096-3445.135.2.314 [PubMed: 16719656]

Botvinick M, & Bylsma LM (2005). Regularization in short-term memory for serial order. Journal of Experimental Psychology: Learning, Memory, and Cognition, 31(2), 351–358. 10.1037/0278-7393.31.2.351 [PubMed: 15755251]

Brady TF, Konkle T, & Alvarez GA (2009). Compression in visual working memory: Using statistical regularities to form more efficient memory representations. Journal of Experimental Psychology: General, 138(4), 487–502. 10.1037/a0016797 [PubMed: 19883132]

Brady TF, & Tenenbaum JB (2013). A probabilistic model of visual working memory: Incorporating higher order regularities into working memory capacity estimates. Psychological Review, 120(1), 85–109. 10.1037/a0030779 [PubMed: 23230888]

Cameron-Faulkner T, Lieven E, & Tomasello M (2003). A construction-based analysis of child directed speech. Cognitive Science, 27(6), 843–873. 10.1207/s15516709cog2706_2

Chase WG, & Simon HA (1973). Perception in chess. Cognitive Psychology, 4(1), 55–81. 10.1016/0010-0285(73)90004-2

Chen Z, & Cowan N (2009). Core verbal working-memory capacity: The limit in words retained without covert articulation. Quarterly Journal of Experimental Psychology: Human Experimental Psychology, 62(7), 1420–1429. 10.1080/17470210802453977

Chomsky N (1957). Syntactic structures. Mouton. 10.1515/9783112316009

Chomsky N (1980). Rules and representations. Behavioral and Brain Sciences, 3(1), 1–15. 10.1017/S0140525X00001515

Christiansen MH (2019). Implicit-statistical learning: A tale of two literatures. Topics in Cognitive Science, 11(3), 468–481. 10.1111/tops.12332 [PubMed: 29630770]

Christiansen MH, & Chater N (2016). The now-or-never bottleneck: A fundamental constraint on language. Behavioral and Brain Sciences, 39, e62. 10.1017/S0140525X1500031X [PubMed: 25869618]

Conway CM, Bauernschmidt A, Huang SS, & Pisoni DB (2010). Implicit statistical learning in language processing: Word predictability is the key. Cognition, 114(3), 356–371. 10.1016/j.cognition.2009.10.009 [PubMed: 19922909]

Cowan N (2001). The magical number 4 in short-term memory: A reconsideration of mental storage capacity. Behavioral and Brain Sciences, 24(1), 87–114. 10.1017/S0140525X01003922 [PubMed: 11515286]

Cowan N, Chen Z, & Rouder JN (2004). Constant capacity in an immediate serial-recall task: A logical sequel to Miller (1956). Psychological Science, 15(9), 634–640. 10.1111/j.0956-7976.2004.00732.x [PubMed: 15327636]

Cowan N, Rouder JN, Blume CL, & Saults JS (2012). Models of verbal working memory capacity: What does it take to make them work? Psychological Review, 119(3), 480–499. 10.1037/a0027791 [PubMed: 22486726]

Dawson C, & Gerken L (2009). From domain-generality to domain-sensitivity: 4-month-olds learn an abstract repetition rule in music that 7-month-olds do not. Cognition, 111(3), 378–382. 10.1016/j.cognition.2009.02.010 [PubMed: 19338982]

De Diego Balaguer R, Toro JM, Rodriguez-Fornells A, & Bachoud-Lévi AC (2007). Different neurophysiological mechanisms underlying word and rule extraction from speech. PLoS One, 2(11), e1175. 10.1371/journal.pone.0001175 [PubMed: 18000546]

de Diego-Balaguer R, Rodríguez-Fornells A, & Bachoud-Lévi AC (2015). Prosodic cues enhance rule learning by changing speech segmentation mechanisms. Frontiers in Psychology, 6, 1478. 10.3389/fpsyg.2015.01478 [PubMed: 26483731]

Dollaghan C, & Campbell TF (1998). Nonword repetition and child language impairment. Journal of Speech, Language, and Hearing Research, 41(5), 1136–1146. 10.1044/jslhr.4105.1136

Ellis Weismer S, Tomblin JB, Zhang X, Buckwalter P, Chynoweth JG, & Jones M (2000). Nonword repetition performance in school-age children with and without language impairment. Journal of Speech, Language, and Hearing Research, 43(4), 865–878. 10.1044/jslhr.4304.865

Endress AD, & Bonatti LL (2007). Rapid learning of syllable classes from a perceptually continuous speech stream. Cognition, 105(2), 247–299. 10.1016/j.cognition.2006.09.010 [PubMed: 17083927]

Endress AD, & Bonatti LL (2016). Words, rules, and mechanisms of language acquisition. Wiley Interdisciplinary Reviews: Cognitive Science, 7(1), 19–35. 10.1002/wcs.1376 [PubMed: 26683248]

Endress AD, Cahill D, Block S, Watumull J, & Hauser MD (2009). Evidence of an evolutionary precursor to human language affixation in a non-human primate. Biology Letters, 5(6), 749–751. 10.1098/rsbl.2009.0445 [PubMed: 19586963]

Endress AD, & Mehler J (2009). The surprising power of statistical learning: When fragment knowledge leads to false memories of unheard words. Journal of Memory and Language, 60(3), 351–367. 10.1016/j.jml.2008.10.003

Endress AD, Nespor M, & Mehler J (2009). Perceptual and memory constraints on language acquisition. Trends in Cognitive Sciences, 13(8), 348–353. 10.1016/j.tics.2009.05.005 [PubMed: 19647474]

Endress AD, Scholl BJ, & Mehler J (2005). The role of salience in the extraction of algebraic rules. Journal of Psychology: General, 134(3), 406–419. 10.1037/0096-3445.134.3.406

Fló A (2021). Evidence of ordinal position encoding of sequences extracted from continuous speech. Cognition, 213, 104646. 10.1016/j.cognition.2021.104646 [PubMed: 33707004]

Frank MC, Goldwater S, Griffiths TL, & Tenenbaum JB (2010). Modeling human performance in statistical word segmentation. Cognition, 117(2), 107–125. 10.1016/j.cognition.2010.07.005 [PubMed: 20832060]

French RM, Addyman C, & Mareschal D (2011). TRACX: A recognition-based connectionist framework for sequence segmentation and chunk extraction. Psychological Review, 118(4), 614–636. 10.1037/a0025255 [PubMed: 22003842]

Frost R, Armstrong BC, & Christiansen MH (2019). Statistical learning research: A critical review and possible new directions. Psychological Bulletin, 145(12), 1128–1153. 10.1037/bul0000210 [PubMed: 31580089]

Frost R, Armstrong BC, Siegelman N, & Christiansen MH (2015). Domain generality versus modality specificity: The paradox of statistical learning. Trends in Cognitive Sciences, 19(3), 117–125. 10.1016/j.tics.2014.12.010 [PubMed: 25631249]

Frost RLA, Isbilen ES, Monaghan P, & Christiansen MH (2019). Testing the limits of nonadjacent dependency learning: statistical segmentation and generalization across domains. In Goel A, Seifert C, & Freksa C (Eds.), Proceedings of the 41st Annual Conference of the Cognitive Science Society (pp. 1787–1793). Cognitive Science Society.

Frost RLA, Jessop A, Durrant S, Peter MS, Bidgood A, Pine JM, Rowland CF, & Monaghan P (2020). Nonadjacent dependency learning in infancy, and its link to language development. Cognitive Psychology, 120, 101291. 10.1016/j.cogpsych.2020.101291 [PubMed: 32197131]

Frost RLA, & Monaghan P (2016). Simultaneous segmentation and generalisation of nonadjacent dependencies from continuous speech. Cognition, 147, 70–74. 10.1016/j.cognition.2015.11.010 [PubMed: 26638049]

Gathercole SE, Frankish CR, Pickering SJ, & Peaker S (1999). Phonotactic influences on short-term memory. Journal of Experimental Psychology: Learning, Memory, and Cognition, 25(1), 84–95. 10.1037/0278-7393.25.1.84 [PubMed: 9949710]

Giroux I, & Rey A (2009). Lexical and sublexical units in speech perception. Cognitive Science, 33(2), 260–272. 10.1111/j.1551-6709.2009.01012.x [PubMed: 21585470]

Gobet F, & Simon HA (1998). Expert chess memory: Revisiting the chunking hypothesis. Memory, 6(3), 225–255. 10.1080/741942359 [PubMed: 9709441]

Goldberg AE (2006). Constructions at work: The nature of generalization in language. Oxford University Press.

Gómez RL (2002). Variability and detection of invariant structure. Psychological Science, 13(5), 431–436. 10.1111/1467-9280.00476 [PubMed: 12219809]

Gómez RL, & Gerken L (1999). Artificial grammar learning by 1-year-olds leads to specific and abstract knowledge. Cognition, 70(2), 109–135. 10.1016/S0010-0277(99)00003-7 [PubMed: 10349760]

Gómez R, & Maye J (2005). The developmental trajectory of nonadjacent dependency learning. Infancy, 7(2), 183–206. 10.1207/s15327078in0702_4 [PubMed: 33430549]

Goodsitt JV, Morse PA, Ver Hoeve JN, & Cowan N (1984). Infant speech recognition in multisyllabic contexts. Child Development, 55(3), 903–910. 10.2307/1130141 [PubMed: 6734325]

Greene RL, Elliot CL, & Smith MD (1988). When do interleaved suffixes improve recall? Journal of Memory and Language, 27(5), 560–571. 10.1016/0749-596X(88)90026-5

Grimm R, Cassani G, Gillis S, & Daelemans W (2017). Facilitatory effects of multi-word units in lexical processing and word learning: A computational investigation. Frontiers in Psychology, 8, 555. 10.3389/fpsyg.2017.00555 [PubMed: 28450842]

Hitch GJ (1975). The role of attention in visual and auditory suffix effects. Memory & Cognition, 3(5), 501–505. 10.3758/BF03197521 [PubMed: 24203871]

Hockett CF (1959). Animal languages and human language. Human Biology, 31(1), 32–39. [PubMed: 13640650]

Hollingworth A, & Henderson JM (2003). Testing a conceptual locus for the inconsistent object change detection advantage in real-world scenes. Memory & Cognition, 31(6), 930–940. 10.3758/BF03196446 [PubMed: 14651300]

Hulme C, Roodenrys S, Schweickert R, Brown GD, Martin M, & Stuart G (1997). Word-frequency effects on short-term memory tasks: Evidence for a redintegration process in immediate serial recall. Journal of Experimental Psychology: Learning, Memory, and Cognition, 23(5), 1217–1232. 10.1037/0278-7393.23.5.1217 [PubMed: 9293631]

Isbilen ES, McCauley SM, Kidd E, & Christiansen MH (2020). Statistically-induced chunking recall: A memory-based approach to statistical learning. Cognitive Science, 44(7), e12848. 10.1111/cogs.12848 [PubMed: 32608077]

Jones G (2012). Why chunking should be considered as an explanation for developmental change before short-term memory capacity and processing speed. Frontiers in Psychology, 3, 167. 10.3389/fpsyg.2012.00167 [PubMed: 22715331]

Jones G (2016). The influence of children's exposure to language from two to six years: The case of nonword repetition. Cognition, 153, 79–88. 10.1016/j.cognition.2016.04.017 [PubMed: 27155560]

Jones G, Gobet F, Freudenthal D, Watson SE, & Pine JM (2014). Why computational models are better than verbal theories: The case of nonword repetition. Developmental Science, 17(2), 298–310. 10.1111/desc.12111 [PubMed: 24238080]

Jones G, & Macken B (2015). Questioning short-term memory and its measurement: Why digit span measures long-term associative learning. Cognition, 144, 1–13. 10.1016/j.cognition.2015.07.009 [PubMed: 26209910]

Kidd E, Arciuli J, Christiansen MH, Isbilen ES, Revius K, & Smithson M (2020). Measuring children's auditory statistical learning via serial recall. Journal of Experimental Child Psychology, 200, 104964. 10.1016/j.jecp.2020.104964 [PubMed: 32858420]

Kinder A, & Assmann A (2000). Learning artificial grammars: No evidence for the acquisition of rules. Memory & Cognition, 28(8), 1321–1332. 10.3758/BF03211833 [PubMed: 11219960]

Knowlton BJ, & Squire LR (1994). The information acquired during artificial grammar learning. Journal of Experimental Psychology: Learning, Memory, and Cognition, 20(1), 79–91. 10.1037/0278-7393.20.1.79 [PubMed: 8138790]

Knowlton BJ, & Squire LR (1996). Artificial grammar learning depends on implicit acquisition of both abstract and exemplar-specific information. Journal of Experimental Psychology: Learning, Memory, and Cognition, 22(1), 169–181. 10.1037/0278-7393.22.1.169 [PubMed: 8648284]

Kol S, Nir B, & Wintner S (2014). Computational evaluation of the traceback method. Journal of Child Language, 41(1), 176–199. 10.1017/S0305000912000694 [PubMed: 23343571]

Kuhn G, & Dienes Z (2005). Implicit learning of nonlocal musical rules: Implicitly learning more than chunks. Journal of Experimental Psychology: Learning, Memory, and Cognition, 31(6), 1417–1432. 10.1037/0278-7393.31.6.1417 [PubMed: 16393055]

Kuznetsova A, Brockhoff PB, & Christensen RHB (2017). lmerTest package: Tests in linear mixed effects models. Journal of Statistical Software, 82(13), 1–26. 10.18637/jss.v082.i13

Lazartigues L, Lavigne F, Aguilar C, Cowan N, & Mathy F (2021). Benefits and pitfalls of data compression in visual working memory. Attention, Perception & Psychophysics, 83(7), 2843–2864. 10.3758/s13414-021-02333-x

Lieven E (2016). Usage-based approaches to language development: Where do we go from here? Language and Cognition, 8(3), 346–368. 10.1017/langcog.2016.16

Lieven E, Behrens H, Speares J, & Tomasello M (2003). Early syntactic creativity: A usage-based approach. Journal of Child Language, 30(2), 333–370. 10.1017/S0305000903005592 [PubMed: 12846301]

Lieven EV, Pine JM, & Baldwin G (1997). Lexically based learning and early grammatical development. Journal of Child Language, 24(1), 187–219. 10.1017/S0305000996002930 [PubMed: 9154014]

Majerus S, van der Linden M, Mulder L, Meulemans T, & Peters F (2004). Verbal short-term memory reflects the sublexical organization of the phonological language network: Evidence from an incidental phonotactic learning paradigm. Journal of Memory and Language, 51(2), 297–306. 10.1016/j.jml.2004.05.002

Marchetto E, & Bonatti LL (2013). Words and possible words in early language acquisition. Cognitive Psychology, 67(3), 130–150. 10.1016/j.cogpsych.2013.08.001 [PubMed: 24041871]

Marchetto E, & Bonatti LL (2015). Finding words and word structure in artificial speech: The development of infants' sensitivity to morphosyntactic regularities. Journal of Child Language, 42(4), 873–902. 10.1017/S0305000914000452 [PubMed: 25300736]

McCauley SM, & Christiansen MH (2014). Acquiring formulaic language: A computational model. The Mental Lexicon, 9(3), 419–436. 10.1075/ml.9.3.03mcc

McCauley SM, & Christiansen MH (2019a). Language learning as language use: A cross-linguistic model of child language development. Psychological Review, 126(1), 1–51. 10.1037/rev0000126 [PubMed: 30604987]

McCauley SM, & Christiansen MH (2019b). Modeling children's early linguistic productivity through the automatic discovery and use of lexically based frames. In Goel A, Seifert C, & Freksa C (Eds.), Proceedings of the 41st Annual Conference of the Cognitive Science Society (pp. 782–788). Cognitive Science Society.

Miller GA (1956). The magical number seven plus or minus two: Some limits on our capacity for processing information. Psychological Review, 63(2), 81–97. 10.1037/h0043158 [PubMed: 13310704]

Murray DJ (1966). Intralist interference and rehearsal time in short-term memory. Canadian Journal of Psychology, 20(4), 413–426. 10.1037/h0082952 [PubMed: 5980735]

Newport EL, & Aslin RN (2004). Learning at a distance I. Statistical learning of nonadjacent dependencies. Cognitive Psychology, 48(2), 127–162. 10.1016/S0010-0285(03)00128-2 [PubMed: 14732409]

Nicholls AP, Parmentier FB, Jones DM, & Tremblay S (2005). Visual distraction and visuo-spatial memory: A sandwich effect. Memory, 13, 357–363. [PubMed: 15948621]

Norris D, Kalm K, & Hall J (2020). Chunking and redintegration in verbal short-term memory. Journal of Experimental Psychology: Learning, Memory, and Cognition, 46(5), 872–893. 10.1037/xlm0000762 [PubMed: 31566390]

Oliva A (2005). Gist of the scene. In Itti L, Rees G, & Tsotsos JK (Eds.), Neurobiology of attention (pp. 251–256). Elsevier. 10.1016/B978-012375731-9/50045-8

Onnis L, Monaghan P, Christiansen MH, & Chater N (2004). Variability is the spice of learning, and a crucial ingredient for detecting and generalizing in nonadjacent dependencies. In Forbus KD, Gentner D, & Regier T (Eds.), Proceedings of the 26th Annual Conference of the Cognitive Science Society (pp. 1047–1052). Lawrence Erlbaum.

Onnis L, Monaghan P, Richmond K, & Chater N (2005). Phonology impacts segmentation in online speech processing. Journal of Memory and Language, 53(2), 225–237. 10.1016/j.jml.2005.02.011

Orbán G, Fiser J, Aslin RN, & Lengyel M (2008). Bayesian learning of visual chunks by human observers. Proceedings of the National Academy of Sciences of the United States of America, 105(7), 2745–2750. 10.1073/pnas.0708424105 [PubMed: 18268353]

Pelucchi B, Hay JF, & Saffran JR (2009). Statistical learning in a natural language by 8-month-old infants. Child Development, 80(3), 674–685. 10.1111/j.1467-8624.2009.01290.x [PubMed: 19489896]

Peña M, Bonatti LL, Nespor M, & Mehler J (2002). Signal-driven computations in speech processing. Science, 298(5593), 604–607. 10.1126/science.1072901 [PubMed: 12202684]

Perruchet P (2019). What mechanisms underlie implicit statistical learning? Transitional probabilities versus chunks in language learning. Topics in Cognitive Science, 11(3), 520–535. 10.1111/tops.12403 [PubMed: 30569631]

Perruchet P, & Desaulty S (2008). A role for backward transitional probabilities in word segmentation? Memory & Cognition, 36(7), 1299–1305. 10.3758/MC.36.7.1299 [PubMed: 18927044]

Perruchet P, & Pacton S (2006). Implicit learning and statistical learning: One phenomenon, two approaches. Trends in Cognitive Sciences, 10(5), 233–238. 10.1016/j.tics.2006.03.006 [PubMed: 16616590]

Perruchet P, & Poulin-Charronnat B (2012). Beyond transitional probability computations: Extracting word-like units when only statistical information is available. Journal of Memory and Language, 66(4), 807–818. 10.1016/j.jml.2012.02.010

Perruchet P, Tyler MD, Galland N, & Peereman R (2004). Learning nonadjacent dependencies: No need for algebraic-like computations. Journal of Experimental Psychology: General, 133(4), 573–583. 10.1037/0096-3445.133.4.573 [PubMed: 15584807]

Perruchet P, & Vinter A (1998). PARSER: A model for word segmentation. Journal of Memory and Language, 39(2), 246–263. 10.1006/jmla.1998.2576

Poggio T, & Bizzi E (2004). Generalization in vision and motor control. Nature, 431(7010), 768–774. 10.1038/nature03014 [PubMed: 15483597]

R Core Team. (2020). R: A language and environment for statistical computing. Retrieved January 1, 2018, from http://www.R-project.org/

Radulescu S, Wijnen F, & Avrutin S (2020). Patterns bit by bit: An entropy model for rule induction. Language Learning and Development, 16(2), 109–140. 10.1080/15475441.2019.1695620

Rodríguez-Fornells A, Cunillera T, Mestres-Missé A, & de Diego-Balaguer R (2009). Neurophysiological mechanisms involved in language learning in adults. Philosophical Transactions of the Royal Society of London. Series B, Biological Sciences, 364(1536), 3711–3735. 10.1098/rstb.2009.0130 [PubMed: 19933142]

Romberg AR, & Saffran JR (2013). All together now: Concurrent learning of multiple structures in an artificial language. Cognitive Science, 37(7), 1290–1320. 10.1111/cogs.12050 [PubMed: 23772795]

Saffran JR (2001). Words in a sea of sounds: The output of infant statistical learning. Cognition, 81(2), 149–169. 10.1016/S0010-0277(01)00132-9 [PubMed: 11376640]

Saffran JR (2002). Constraints on statistical language learning. Journal of Memory and Language, 47(1), 172–196. 10.1006/jmla.2001.2839

Saffran JR, Aslin RN, & Newport EL (1996). Statistical learning by 8-month-old infants. Science, 274(5294), 1926–1928. 10.1126/science.274.5294.1926 [PubMed: 8943209]

Saffran JR, Pollak SD, Seibel RL, & Shkolnik A (2007). Dog is a dog is a dog: Infant rule learning is not specific to language. Cognition, 105(3), 669–680. 10.1016/j.cognition.2006.11.004 [PubMed: 17188676]

Schneider W, Eschman A, & Zuccolotto A (2002). E-prime user's guide. Psychology Software Tools.

Siegelman N, Bogaerts L, Armstrong BC, & Frost R (2019). What exactly is learned in visual statistical learning? Insights from Bayesian modeling. Cognition, 192, 104002. 10.1016/j.cognition.2019.06.014

Slone LK, & Johnson SP (2018). When learning goes beyond statistics: Infants represent visual sequences in terms of chunks. Cognition, 178, 92–102. 10.1016/j.cognition.2018.05.016 [PubMed: 29842989]

Slone L, & Johnson SP (2015). Statistical and chunking processes in adults' visual sequence learning. In Noelle DC & Dale R (Eds.), Proceedings of the 37th Annual Conference of the Cognitive Science Society (pp. 2218–2223). Cognitive Science Society.

Thalmann M, Souza AS, & Oberauer K (2019). How does chunking help working memory? Journal of Experimental Psychology: Learning, Memory, and Cognition, 45(1), 37–55. 10.1037/xlm0000578 [PubMed: 29698045]

Thiessen ED, & Pavlik PI Jr. (2013). iMinerva: A mathematical model of distributional statistical learning. Cognitive Science, 37(2), 310–343. 10.1111/cogs.12011 [PubMed: 23126517]

Tomasello M (Ed.). (2003). Introduction: Some surprises for psychologists. New psychology of language: Cognitive and functional approaches to language structure (pp. 1–14). Lawrence Erlbaum. 10.4324/9781410606921-3

Trotter AS, Monaghan P, Beckers GJL, & Christiansen MH (2020). Exploring variation between artificial grammar learning experiments: Outlining a meta-analysis approach. Topics in Cognitive Science, 12(3), 875–893. 10.1111/tops.12454 [PubMed: 31495072]

Van den Bos E, Christiansen MH, & Misyak JB (2012). Statistical learning of probabilistic nonadjacent dependencies by multiple-cue integration. Journal of Memory and Language, 67(4), 507–520. 10.1016/j.jml.2012.07.008

Vuong LC, Meyer AS, & Christiansen MH (2016). Concurrent statistical learning of adjacent and nonadjacent dependencies. Language Learning, 66(1), 8–30. 10.1111/lang.12137

Wang FH, Zevin J, & Mintz TH (2019). Successfully learning nonadjacent dependencies in a continuous artificial language stream. Cognitive Psychology, 113, 101223. 10.1016/j.cogpsych.2019.101223 [PubMed: 31212192]

Wilson B, Spierings M, Ravignani A, Mueller JL, Mintz TH, Wijnen F, van der Kant A, Smith K, & Rey A (2020). Non-adjacent dependency learning in humans and other animals. Topics in Cognitive Science, 12(3), 843–858. 10.1111/tops.12381 [PubMed: 32729673]

Wolff JG (1982). Language acquisition, data compression and generalization. Language & Communication, 2(1), 57–89. 10.1016/0271-5309(82)90035-0

Word Learning
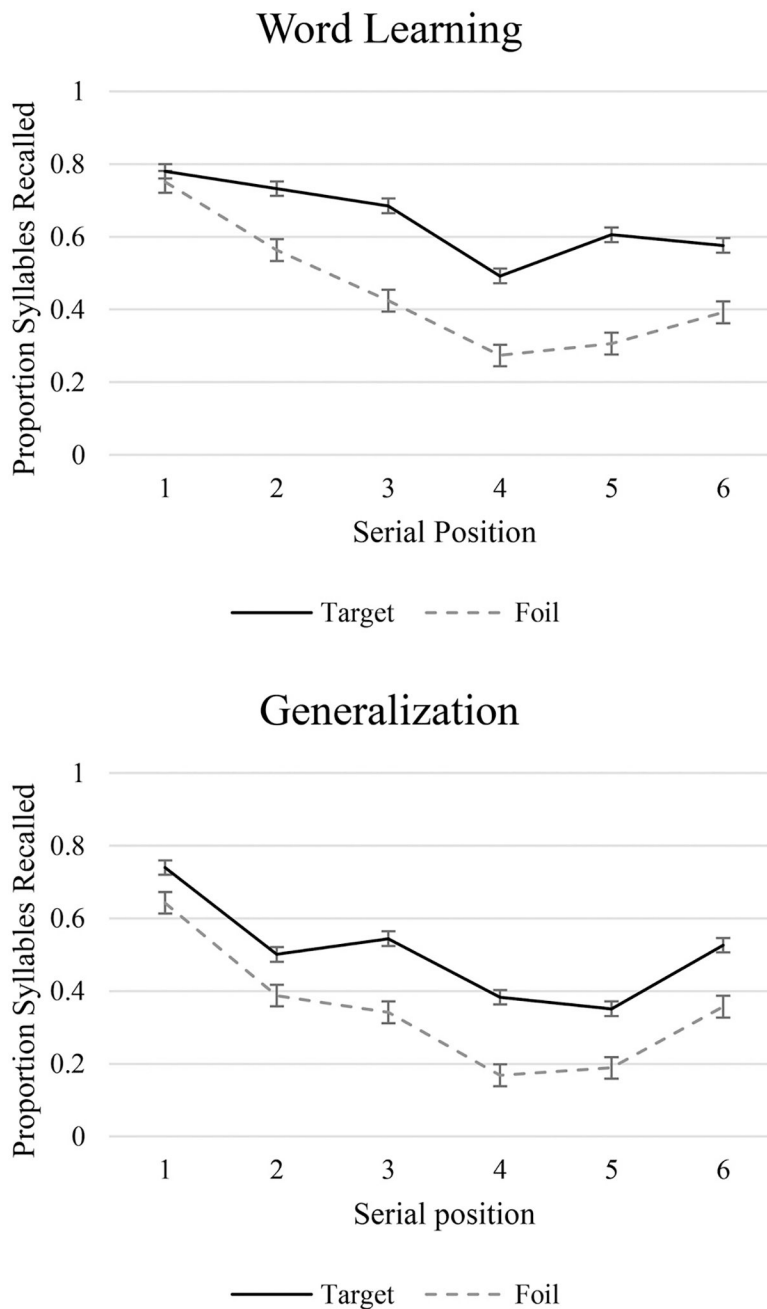
Generalization

Figure 1.

Serial Position Curves Showing the Accuracy of Recall on the SICR Task

Note. On the word learning and generalization trials, accuracy was higher for the target items (which follow the statistics of the artificial language) than it was for the foil items. Error bars reflect standard error.

Word Learning
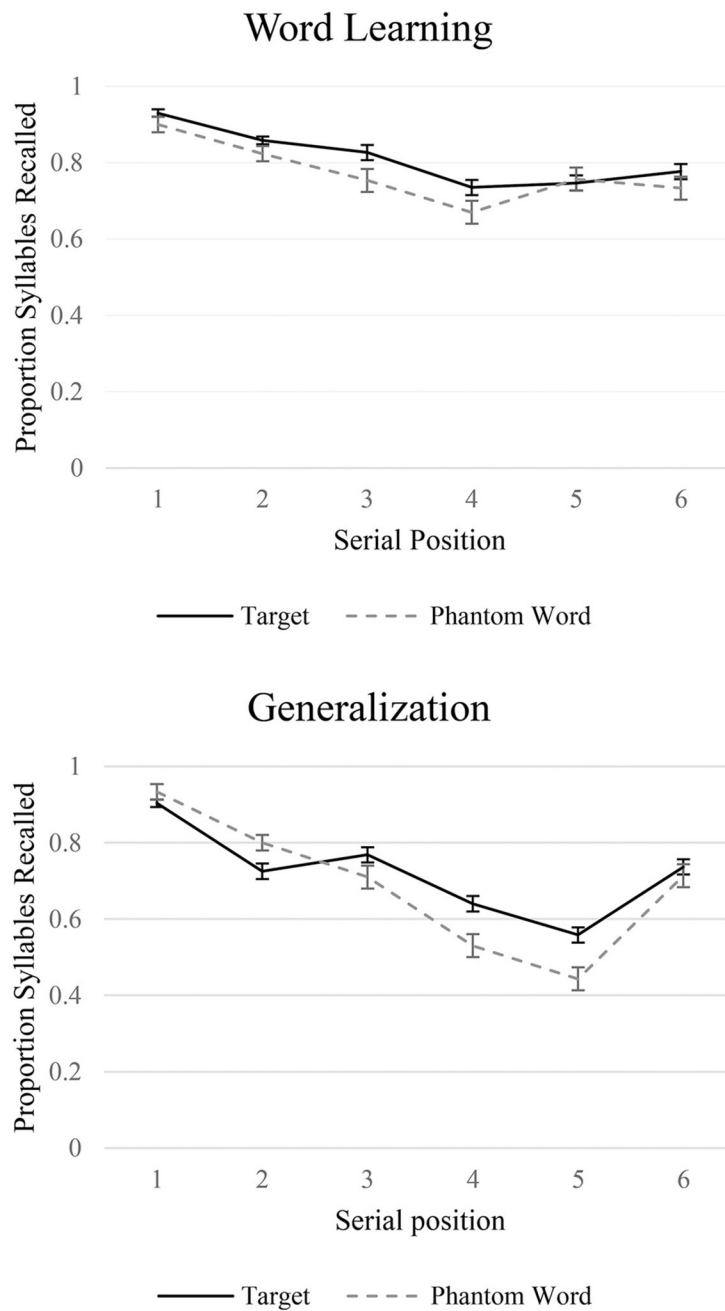
Generalization

Figure 2.

SICR Serial Position Curves for the Word Learning and Generalization Trials by Item Type (Target Versus Phantom Word Strings)

Note. Error bars reflect standard errors.

Table 1

Summary Statistics for SICR by Item Type (Proportion Correct)

Item type	Syllables			Bigrams			Trigrams			NADs		
	M	*SD*	Range	*M*	*SD*	Range	*M*	*SD*	Range	*M*	*SD*	Range
Word learning												
Target	.22	.07	.06–33	.17	.08	0–33	.14	.09	0–31	.16	.09	.02–31
Foil	.09	.04	.02–17	.05	.04	0–15	.04	.04	0–13	.05	.05	0–15
Generalization												
Target	.18	.07	.05–33	.11	.08	0–32	.09	.08	0–31	.13	.09	.02–33
Foil	.05	.03	.01–12	.03	.03	0–10	.02	.03	0–10	.03	.03	0–10

Table 2

Summary Statistics for 2AFC by Item Type (Proportion Correct)

Item type	*M*	*SD*	Range
Word learning	.84	.13	.56–1
Generalization	.70	.21	.22–1

Table 3

Summary Statistics for SICR by Item Type (Proportion Correct)

Item type	Syllables			Bigrams			Trigrams			NADs		
	M	SD	Range	M	SD	Range	M	SD	Range	M	SD	Range
Word learning												
Target	.25	.05	.13–.31	.23	.06	.08–.32	.21	.07	.06–.31	.22	.06	.06–.31
Phantom	.12	.03	.03–.15	.10	.04	.02–.16	.09	.04	.02–.15	.10	.04	.02–.15
Generalization												
Target	.22	.06	.08–.31	.18	.07	.04–.32	.16	.08	.02–.31	.20	.07	.06–.31
Phantom	.11	.03	.04–.15	.08	.04	0–.16	.07	.04	0–.15	.09	.04	.02–.15

Table 4

Summary Statistics for 2AFC by Item Type

Item type	M	SD	Range
Word	.61	.16	.33–1
Generalization	.53	.17	0–1