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The interaction between temporal grouping and phonotactic chunking in short-term serial order memory for novel verbal sequences

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Abstract

The current study investigated the ways long-term memory contributes to short-term serial order memory of novel verbal sequences, focusing on long-term knowledge of *bi-element frequency*, that is, co-occurrence frequency of two consecutive elements in a linguistic environment. Participants performed two types of immediate serial recall of nine-element (nine-mora) sequences: low bi-mora frequency sequences where all eight associations between the nine morae were low frequency, and mixed bi-mora frequency sequences, with high-frequency associations for six of the eight bi-morae. Experiment 1 confirmed the bi-directional bi-mora frequency effect, meaning better recall performance for morae having high-frequency association with either the preceding mora (forward association) or the following mora (backward association). In Experiment 2, two temporal pauses were inserted in each list to disrupt high-frequency associations with the preceding mora or the following mora. The results showed that the bi-element frequency effect diminished when the high-frequency backward association was disrupted but the effect remained when the high-frequency forward association was disrupted. We discussed the possible mechanisms underlying the asymmetric influence of temporal pauses on interactions between short-term memory and linguistic long-term memory.

 (179/200 words)

Introduction

A fundamental functional requirement for language processing is serial order control (Lashley, 1951). Phonemes are ordered into a syllable, syllables into a word, words into a sentence, and so forth. It is notable that such serial order control in language processing is inevitably based on temporary retention of serial order information. We need to hold the order of phonemes within a word just before the production of the word and to retain the order of words during oral communication. This observation has guided a line of inquiry into short-term verbal serial order memory (see, Gathercole & Baddeley, 1993; Baddeley, 2012), and led to detailed computational models of serial order memory (e.g., Botvinick & Plaut, 2006; Burgess & Hitch, 1999; 2006; Farrell, 2012; Henson, 1998; Lewandowsky & Murdock, 1989; Page & Norris, 1998; 2009, for a review, see Hurlstone, Hitch, & Baddeley, 2014). Another fact of note is that the short-term retention of serial order information is supported by long-term linguistic knowledge. This is exemplified by the influence of phonotactic knowledge - a verbal sequence that contains high-frequency phonotactic patterns leads to better short-term memory performance than that with low-frequency patterns (Gathercole, Frankish, Pickering, & Peaker, 1999; Majerus & Van der Linden, 2003; Nakayama, Tanida, & Saito, 2015; Tanida, Ueno, Lambon Ralph, & Saito, 2015; Thorn, Gathercole, & Frankish, 2005). The present study investigated how long-term serial order memory contributes to short-term serial order memory. Specifically, we examined what mechanism underlies a *bi-element frequency effect* on Short Term Memory (STM) by seeking a boundary condition for the effect. We focused on the dependency of the bi-element frequency effect on temporal grouping by pauses.

Bi-element frequency refers to the co-occurrence frequency of two consecutive elements in a given environment (e.g., two successive phonemes in a linguistic environment). In general, the cognitive system is able to utilize information redundancy in the environment

to achieve efficient processing by forming chunks (Miller, 1956). An example of such bi-element frequency effects and chunking is the bi-phone frequency effect in English (e.g., Gathercole, et al., 1999; Thorn, et al., 2005). In native English-speakers, recall performance of immediate serial recall is better for lists of consonant-vowel-consonant (CVC) nonwords composed of two bi-phonemes (CV and VC) that occur frequently in English words (e.g., 'bip', made from the concatenating frequent bi-phonemes 'bi' and 'ip') than nonwords composed of infrequent bi-phonemes (e.g., 'bez' made from the infrequent bi-phonemes 'be' and 'ez'). The element could be a consonant letter, leading to the bi-gram frequency effect (Baddeley, Conrad, & Hull, 1965). The element also could vary cross-linguistically. The basic element in Japanese phonology is a mora[1] of a sub-syllabic structure, and the bi-mora frequency effect is found in Japanese-speakers (e.g., Nakayama, et al., 2015; Tanida, et al., 2015). Laboratory learning with artificial elements could be a source of chunking and a bi-element frequency effect as well (Chen & Cowan, 2009; Majerus, Van der Linden, Mulder, Meulemans, & Peters, 2004). For example, in an incidental learning experiment (Majerus et al., 2004), children and adults were exposed to a stream of syllables that followed artificial phonotactics (e.g., a phoneme could follow only half of the other phonemes). Subsequent immediate serial recall of nonwords were better for legal nonwords, where successive syllables followed the artificial phonotactics, than illegal nonwords. Hereafter, we refer to this type of effects as the *bi-element frequency effect* in order to express it generically, regardless of its operating unit.

Bi-element frequency also affects speech recognition and production. For recognition, reaction time (RT) by English speakers conducting same–different judgments of two successive nonwords was faster when CVC nonwords were made from frequent rather than

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[1] A Japanese mora consists of a vocalic nucleus, a vowel with onset consonant, a nasal consonant /N/ (only for syllabic coda), or a geminate consonant /Q/. A long vowel /R/ is counted as two morae.

infrequent bi-phones (Luce & Large, 2001). In addition, bi-element frequency provides a cue for recognising a word from a speech stream (Perruchet & Vinter, 1998; Saffran, Aslin, & Newport, 1996). For production, faster RT was demonstrated through reading aloud tri-moraic nonwords made by concatenating frequent rather than infrequent bi-morae in Japanese (Tamaoka & Makioka, 2009). These findings suggest that long-term knowledge of bi-element frequency plays an important role in sub-lexical level chunking, which constrains the order of bi-elements (i.e., which elements precede or follow an element). However, the way by which learned chunks are detected and how they contribute to short-term retention of a novel sequence is still to be explored.

Botvinick and Plaut (2006; see also Botvinick, 2005) and Nakayama, et al. (2015) explicitly distinguished two kinds of bi-element frequency effect: the *forward association frequency effect* and *backward association frequency effect*. In a sequence, a specific item (e.g., X) adjoins both the preceding (e.g., A) and following items (e.g., B). Therefore, the recall of X would be affected by two types of bi-element frequency. One is the forward association frequency of a bi-element composed of the item and the preceding item (e.g., AX frequency). Another is the backward association frequency of a bi-element composed of the item and the following item (e.g., XB frequency). These effects are predicted by some models of serial order memory. The forward association frequency effect is expected by the classic forward chaining account (e.g., Lewandowsky & Murdock, 1989, see also Baddeley et al., 1965), if it is extended to a long-term item-to-item association whereby the first element cues the second one. Other types of models can account for both effects. These models implement a recognition process where *gestalt-like* long-term representation is selected or re-organised at each presentation of a novel item (Botvinick & Plaut, 2006; Burgess & Hitch, 2006; Page & Norris, 2009). Such recognition is assumed to allow a later item to modify representation of earlier items (Botvinick & Plaut, 2006).

If chunk organization is applied to a bi-element level, it is expected that not only the second but also the first element can receive a long-term knowledge contribution, leading to forward and backward association frequency effects, respectively. Nakayama, et al. (2015) offered evidence for bi-element level chunking on immediate serial recall by Japanese speakers. They systematically manipulated bi-element (i.e., bi-mora) frequency within four-mora nonwords and demonstrated the contribution of forward and backward associations to the recall of each mora.

In the context of speech recognition and segmentation, some models implement mechanisms for both directions of effects. PARSYN (Luce, Goldinger, Auer, & Vitevitch, 2000) is a recognition model that realized a competitive inhibitory effect on word recognition processes caused by the presence of neighbours at the lexical level as well as a facilitative phonotactic effect at the phonological level. In this model, allophone candidates pooled in each temporal position are interconnected with, and thus interactively activate, elements in preceding and following positions, and are weighted by forward and backward transition probabilities. Therefore, activation of an element in a given temporal position depends on its transitional probabilities with adjacent elements on both sides. It has been reported that the two types of transitional probabilities contribute to word segmentation from a speech stream. Perruchet and Desaulty (2008) had participants hear a speech stream that consisted of a series of bi-syllabic novel 'words'. Those 'words' were composed in accordance with artificial phonotactics, manipulating both forward and backward transitional probability. Even when only backward (or forward) transitional probability provided a segmentation cue, participants could recognise the bi-syllabic 'words' in the test phase. Notably, backward transitional probability learning has been simulated by some models, including a simple recurrent network (French, Addyman, & Mareschal, 2011; Perruchet & Vinter, 1998; Plaut & Vande Velde, 2017).

In sum, the distinction of forward and backward association frequency is critical in constraining theories of serial order memory and speech recognition. Here, we first attempted to confirm the generality of bi-directional bi-element frequency effects. In the context of STM, the backward association frequency effect is demonstrated after laboratory learning (Botvinick, 2005) or with visual presentation and written recall of natural language materials (Nakayama et al., 2015). We aimed to replicate the backward association frequency effect with auditory presentation and oral recall of natural language materials. We then tested how the bi-element frequency effect interacts with temporal pause and how the interaction might differ between forward and backward association frequency.

The main purpose of the present study is to investigate the boundary condition for these bi-directional bi-element frequency effects. For the use of long-term representation of frequent bi-elements, it would be necessary to detect/recognise the bi-element structure embedded in a speech sequence. No research, however, has yet directly investigated how the recognition of bi-element structures in a memory sequence affects the usage of bi-directional bi-element frequency knowledge. We, therefore, disrupted the detection/recognition of the bi-element chunk at presentation, and aimed to examine what would happen on the bi-element frequency effect when bi-element chunks were not recognised.

A potential important factor for recognising the bi-element chunk is temporal grouping. Even in early speech perception, infants recognise a sequence between temporal pauses within a speech stream as a single unit but a sequence including a temporal pause not as a single unit (Hirsh-Pasek, Nelson, Jusczyk, Cassidy, Druss, & Kennedy, 1987). Thus, temporal grouping provides a *window* that determines a unit in speech. In addition, short-term memory research has provided evidence of an impact of temporal grouping on the way of recognition. On immediate serial recall, typically, a sequence is recalled with a bow-shaped serial position curve. When inserting temporal pauses in a sequence, we can find scalloped-

shaped serial position curves segmented at the positions where temporal pauses were inserted (e.g., Farrell, 2012; Frankish, 1985; Ryan, 1969a; 1969b). Those smaller curves suggested that each (smaller) distinctive sequence between temporal pauses was recognised. In Experiment 2, we inserted temporal pauses in each sequence to systematically interfere with detection of bi-element chunks. For example, in a sequence of AXB, a pause between A and X interferes with a forward association for a specific mora X, disrupting recognition of the chunk 'AX', and a pause between X and B interferes with a backward association for the same mora X, disrupting recognition of the chunk 'XB'. The disruptive effect on recall would be larger when a temporal pause is presented within a high-frequency bi-element than a low-frequency one.

In the current study, Experiment 1 investigated the forward and backward association frequency effects on immediate serial recall of novel sequences of nine items, where one item corresponded to one mora. Two types of nine-item lists were independently manipulated for frequency of forward association and backward association. One was a low-frequency list, where frequency of all bi-morae (i.e., both forward and backward association frequency) was low. The other was a mixed-frequency list, where high- and low-frequency bi-morae were mixed; two bi-morae were of low frequency and six were of high frequency. Consequently, mixed-frequency sequences could have any of three kinds of mora items in terms of association frequency: (1) morae with high-frequency forward and backward associations; (2) morae with high-frequency forward associations but low-frequency backward associations; and (3) morae with low-frequency forward associations but high-frequency backward associations. By comparing recall performance on these mora types with that of morae in low-frequency sequences, one can investigate the effects of forward and backward association frequency. After the effects of bi-directional bi-element frequency were established, Experiment 2 examined the influence of mismatches between temporal grouping

and bi-element frequency chunking on the bi-mora frequency effects by inserting two temporal pauses within each sequence used in Experiment 1.

Experiment 1

Method

    Participants. Twenty-four native Japanese-speaking Kyoto University students participated in Experiment 1 (8 females and 16 males; age range 19–24 years).

    Materials. We prepared 306 sequences in total, each of which was composed of nine morae[2] semi-randomly selected, with the following constraints. All morae had a CV structure, derived from the 62-mora candidate pool of all valid combinations of Japanese vowels (*a, i, u, e,* and *o*) and consonants (*k, s, t, n, h, y, r, w, g, z, d, b,* and *p*). The same consonant did not appear twice within a list, and the same vowel did not appear in successive morae. In addition, each bi-mora token appeared only once through the experiment. Finally, no successive tri-mora was composed of tri-moraic real words or parts of words with quad-moraic or longer structures registered in a Japanese lexical database (Amono & Kondo, 2000).

    With these constraints in place, we constructed two kinds of sequences by manipulating the token frequency of each bi-mora in the memory sequences (Figure 1): *low-frequency* sequences, in which the frequencies of all eight bi-morae were low, and *mixed-frequency* sequences, in which bi-morae frequencies were mixed between high and low. Bi-morae with a token frequency under 2,500 in a Japanese bi-mora frequency database

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[2] The number of morae in a sequence was matched to Tanida, et al. (2015), which identified the bi-mora frequency effect in Japanese university students. An experiment in that study employed three tri-mora nonword sequences for immediate serial recall with auditory presentation and oral recall.

(Tamaoka & Makioka, 2004) were categorized as low frequency and those with a frequency over 25,000, high frequency. We first constructed 51 low- and 51 mixed-frequency sequences. In addition, we generated derivative sequences from these original *seed* sequences: 51 *dextral* and 51 *sinistral* sequences for each low- or mixed-frequency sequence. The method to make stimulus sequences is described below (see also Figure 1).

For the low-frequency sequences, we first made 51 *seed* sequences in which all nine morae were concatenated to create low-frequency bi-mora with each adjacent mora. The *dextral* sequences were generated by moving the final mora in the seed sequence to the first position (with the result that eight of the nine morae in the seed sequence were moved one position closer to the end of the sequence), whereas the *sinistral* sequences were generated by moving the first mora in the seed sequence to the final position (so that eight morae were moved one position closer to the beginning of the sequence). Thus, the component morae and their relative positions in a seed sequence (except for those at the edge positions of the sequences) were kept consistent in the derived dextral and sinistral sequences.

For mixed-frequency sequences, we constructed 51 seed sequences in which nine morae were concatenated so as to create high-frequency bi-morae with each adjacent mora, except for the bi-morae composed of the third and fourth and of the sixth and seventh morae, which were of low frequency. Then we generated the dextral and sinistral sequences from each seed sequence in the same way as the low-frequency bi-mora sequences. Consequently, low-frequency bi-morae were located across the fourth and fifth and the seventh and eighth positions in dextral sequences, and across the second and third and the fifth and sixth positions in sinistral sequences. Through this sliding method, a variety of frequencies of bi-morae with the same serial position was generated across seed, dextral, and sinistral sequences (see Figure 1). The fourth mora, for example, was concatenated within the seed sequences with the preceding (third) mora to compose a low-frequency bi-mora but also

concatenated with the following (fifth) mora to compose a high-frequency bi-mora. In the dextral sequences, the fourth mora was associated with high frequency with the third mora but with low frequency with the fifth mora, whereas in the sinistral sequences, the fourth mora had high-frequency associations with both the third and the fifth mora. Although this manipulation was required only for the mixed-frequency sequences described above, we employed the same sliding method to generate low-frequency sequences for control purposes. Note that the first bi-morae in the dextral sequences and the final bi-morae of sinistral sequences, which were made by concatenating the first and final morae of seed sequences, were of low frequency for low-frequency sequences and of high frequency for mixed-frequency sequences. All prepared seed sequences are provided in Table A of Appendix A, and the average token frequency of the bi-morae employed is shown in Table 1.

Recording and sound editing. A female with perfect pitch hearing pronounced each mora at the pitch of D3. Sound files were cut into 350-ms slices from the onset, and at the offset of sound, a 5-ms fade-out was inserted. The amplitudes of all files were equalized by matching with a randomly selected file. The morae were recorded with MacBook Pro (MB990J/A) and a USB microphone (SNOWBALL-MW, Blue Microphones) and were edited with Adobe Soundbooth CS4. The sampling rate was 44.1 kHz, the sample size was 16 bit, and the number of channels was one. All files used were first heard and transcribed correctly by both the second and third authors, who had never previously listened to the files, demonstrating their comprehensibility.

Procedure. Each participant performed an immediate serial recall task with 102 sequences comprised of 17 seed, 17 dextral, and 17 sinistral mixed- and low-frequency sequences (for 51 each) from the set of 306 prepared sequences. To avoid presenting the same sequences (that is, sequences from the same seed) during the experiment, we randomly categorized sequences to three blocks (A, B, and C), as follows. First, the 102 seed sequences

were randomly divided into the three blocks, with their corresponding dextral and sinistral

sequences (e.g., for a seed sequence 'mo-to-hi-zo-wa-bo-ge-pu-ke', the corresponding dextral

sequence 'ke-mo-to-hi-zo-wa-bo-ge-pu' and the corresponding sinistral sequence 'to-hi-zo-

wa-bo-ge-pu-ke-mo' belonged to the same block). Then, for each participant, we employed

seed, dextral, and sinistral sequences from different blocks, with combinations of sequence

types (seed, dextral, and sinistral) and blocks (A, B, and C) counterbalanced across

participants. Consequently, each participant experienced a specific mora sequence only once.

The order of presentation of sequences was completely random in each experiment. All 62

mora types in the candidate pool were employed among the stimulus sequence sets. The

average of token frequency across mora types was 14.81 and the standard deviation was

3.53.[3]

In each trial, nine morae were presented auditorily through headphones beginning 500

ms after participants pressed the space key. The item duration was 500 ms, with 350 ms of

mora sound followed by 150 ms silence. After the presentation of the list, a cross was

presented on the screen as a recall cue. Participants were required to recall orally all nine

morae in the presented order, even if they needed to guess some of the items. Their responses

were transcribed online by the experimenter and were digitally recorded; after the experiment

was complete, the experimenter checked the recorded responses.

Results and Discussion

Morae recalled correctly in the presented serial position were considered to be correct.

Recall accuracy rates for each position are shown in Figure 2, with recall rates in seed,

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[3] The set of mora items employed was consistent across participants, since every participant
experienced the same mora set sequence as either a seed sequence, the corresponding dextral
sequence, or the corresponding sinistral sequence (e.g., a seed sequence 'mo-to-hi-zo-wa-bo-
ge-pu-ke' might be employed for participant A and the derived dextral sequence 'ke-mo-to-
hi-zo-wa-bo-ge-pu' for participant B).

dextral, and sinistral sequences shown separately for mixed-frequency sequences but averaged for low-frequency sequences. First, in order to establish a foundation for the investigation of the modulating effect of temporal pauses on the bi-element frequency effect in Experiment 2, this result-section tested the bi-element frequency effect under this experimental setting without any pauses while retesting the forward and backward association frequency effects. For statistical analysis, we assigned two types of conditions to each mora: forward association frequency and backward association frequency, either high or low. For example, in mixed-frequency sequences, the third mora of a seed sequence was conditioned with high-frequency forward association but low-frequency backward association. The same third mora in a low-frequency sequence was conditioned, on the other hand, with low-frequency forward and backward associations (see Figure 1).

Forward and backward association frequencies were employed as factors for mixed effect logistic regression analyses (Jaeger, 2008) on recall accuracy of morae. The analyses were performed with the statistical software package R, version 3.2.2 (R Development Core Team, 2015) and the package lme4, version 1.1-12 (Bates, et al., 2016), running on a MacBook Air (MD761J/A) with OS X 10.9.5. The same software and computer were used for the analyses in Experiment 2. Appendix B provides formulae for each model in lme4 format; Table B in Appendix B defines the abbreviations in the formulae. Following Barr, Levy, Scheepers, and Tily (2013), the full random effect model (Formula 1 in Appendix B) was assessed first. The dependent variable was the recall accuracy of each mora item, using a categorical code (0: incorrect, 1: correct). For both fixed and random effect factors, forward and backward association frequencies for each mora were projected using the categorical code for the relevant frequency type (-0.5: low frequency, 0.5: high frequency). Random effects included intercepts and slopes for participants and sequences as well as serial positions (in order to control the influence of serial position). Note that the same sequence ID

was assigned to each seed sequence and to the derived dextral and sinistral sequences. However, the full model did not converge, possibly due to high correlations of the random intercept with random slopes of both forward and backward association frequency factors for serial position. Therefore, we dropped those two random slopes for serial position, and the model converged (Formula 2 in Appendix B). Detailed outcomes of the model analysis are shown in Table 2. In addition, we conducted likelihood ratio tests comparing the employed model and two models that dropped each tested fixed effect term (while keeping all random slopes), following the recommendation of Barr et al. (2013), and obtained identical results; those χ^2s are also reported in Table 2.

Table 2 shows that both forward and backward frequency effects were significant; one can see these significant bi-mora effects in the recall performances shown in Figure 2. Generally, recall performance was higher for all mora positions in mixed-compared to low-frequency sequences. It was true for morae with high-frequency forward and low-frequency backward associations (i.e., the third and sixth morae in seed sequences, the fourth and seventh morae in dextral sequences, and the second and fifth morae in sinistral sequences), where only the forward association was assumed to contribute to the frequency effect. It was also true for morae with low-frequency forward and high-frequency backward associations (i.e., the fourth and seventh morae in seed sequences, the fifth and eighth morae in dextral sequences, and the third and sixth morae in sinistral sequences), where only the backward association would show the effect. These findings indicate that not only forward but also backward association frequency contributes to short-term memory for novel sequences.

Experiment 2

In Experiment 1, we demonstrated *forward and backward association frequency effects* on short-term memory functioning. Next, in Experiment 2, we examined whether the

use of long-term bi-element representations depends on proper segmentation into (and recognition of) the bi-element structures within a sequence. Since segmentation does depend greatly on temporal factors (e.g., insertion of temporal pause), participants' segmentation could be manipulated by inserting two temporal pauses between items in a sequence. If a temporal pause is inserted within a frequent bi-mora structure, the temporally grouped structures will not match with the bi-mora chunk; in this case, the bi-element (bi-mora) chunks in sequences will not be detected or recognised. Consequently, the bi-element frequency effect on recall accuracy will decrease or even disappear.

Method and Prediction

Participants were 24 native Japanese speaking Kyoto University students (8 females and 16 males; age range 19–25 years) who had not participated in Experiment 1. The materials and procedure were identical to those used in Experiment 1 except for the insertion of two 1-s temporal pauses after the third and sixth mora positions (Figure 1). Consequently, for serial positions adjacent to temporal pauses (i.e., the third, fourth, sixth, and seventh positions), either forward or backward associations were interrupted by these pauses. The interrupted associations would not drive long-term representations for the bi-element; thus, any contribution of long-term representations should not work, and the interrupted associations should instead behave as low-frequency associations for purposes of recall, even if their actual bi-element frequency was high.

Results and Discussion

The scoring method for recall accuracy was the same as in Experiment 1. Figure 3 shows the rate of correctly recalled morae at each position, again similar to Experiment 1. We predicted an interference effect of temporal pauses on the bi-element frequency effect when a

temporal pause clashed with a high-frequency association; to investigate this prediction, we performed logistic mixed-effects regression analyses focusing on the interaction between presence of temporal pause and bi-element frequency.

For morae in each serial position in presented sequences, four main effect factors were involved: frequencies of both forward and backward association and the presence or lack of anterior and posterior temporal pause. For example, the third mora in mixed-frequency seed sequences was conditioned by high-frequency forward association, low-frequency backward association, lack of anterior temporal pause, and presence of posterior pause (see Figure 1). For fixed effect terms in the logistic mixed effect regression models, we projected these four main effects as well as interactions between forward association frequency and anterior temporal pause, forward association frequency and posterior temporal pause, backward association frequency and anterior temporal pause, and backward association frequency and posterior temporal pause. Each fixed effect was coded as follows: forward association frequency (-0.5: low frequency, 0.5: high frequency), backward association frequency (-0.5: low frequency, 0.5: high frequency), presence of anterior pause (-0.5: absence, 0.5; present), and presence of posterior pause (-0.5: absence, 0.5: present). The dependent variable was the recall accuracy of each mora, expressed using a categorical code (0: incorrect, 1: correct).

First, we tried to assess the full random effect model, but it was difficult to reach convergence because a long time was needed for calculation due to the many terms involved. Therefore, we assessed the model using only the random intercepts of the eight terms for participants, sequences, and serial positions (Formula 3 in Appendix B). Each random intercept was confirmed by likelihood ratio tests comparing the model with all random intercepts, models without each tested intercept, and the model with all random intercepts

converged.[4] The detailed outcomes are shown in Table 3. In addition, we performed

likelihood ratio tests comparing the employed full model and models dropping each tested

fixed effect term (while keeping all random intercepts), and obtained results identical to those

of the random intercept model. The χ^2s are also reported in Table 3.

As Table 3 shows, we found main effects of forward and backward association

frequency, as in Experiment 1. Morae with high-frequency forward association and morae

with high-frequency backward association showed higher performance than morae with low-

frequency forward and backward association, respectively. However, the main effects of

anterior pause and posterior pause were not significant. Critical to the current prediction,

backward association frequency was significantly attenuated by the presence of posterior

pause (third and sixth morae in Figure 3), as reflected in a significant interaction between

backward association frequency and posterior temporal pause, shown in Table 3. In contrast,

the interaction between backward association frequency and presence of anterior pause was

not significant. Thus, a temporal pause presented within a bi-mora interfered with the

backward association frequency effect. On the other hand, we did not find significant

interactions of forward association frequency with presence of anterior or posterior pause;

forward association can overcome interference of a temporal pause presented within the bi-

mora. This asymmetric result between forward and backward association frequency effects

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[4] Barr, et al. (2013) warn that analyses using models with only random intercepts increase the possibility of false positive. Therefore, following their outline, we performed separate analyses to assess each fixed effect while considering the influence of each tested random slope. We established models with all fixed effects, all random intercepts, and each tested random slope (when models did not converge, we dropped random slopes that were highly correlated with the random intercept or whose correlations were not calculated) and compared them with models dropping each tested fixed effect term, using likelihood ratio tests. We obtained almost the same results, except for the fixed effect of interaction between backward association frequency and posterior pause. Regression analysis of the model with the random slope of the interaction showed that the interaction was marginally significant (p = .08). Table C in Appendix C provides detailed outcomes of the regression analysis and the likelihood ratio test.

suggests that forward association is more robust than backward association against temporal factors. This asymmetric strength of associations might be also reflected in the *z*-values of the results in Experiments 1 and 2.

Finally, we deny that attenuation of the bi-mora frequency effect is due to general improvement of recall performance for morae in low-frequency bi-morae by virtue of the facilitative effect of temporal grouping (e.g., Ryan, 1969a; 1969b; see also Farrell, 2012). Although the baseline of recall performance improved generally via temporal pauses when compared with those in Experiment 1, the significant interaction between the presence of posterior pause and frequency of backward association indicates that the negative influence of temporal pause was not general, but operated only under a specific condition (namely, that a temporal pause be presented within frequent bi-mora associations, as can be seen in Figure 3).

General Discussion

The current study investigated the bi-element (bi-mora) frequency effect on immediate serial recall of novel sequences. First, Experiment 1, in which nine-mora items in novel sequences were auditorily presented with 150 ms inter-stimulus intervals for oral recall, confirmed the presence of two types of bi-mora frequency effect. One was the *forward association frequency effect*: when bi-mora frequency was high, the second mora in the bi-mora showed higher recall than that in a low-frequency bi-mora. The other was the *backward association frequency effect*: when bi-mora frequency was high, the first mora in the bi-mora showed higher recall rate than that in a low-frequency bi-mora. These findings indicate that long-term sub-lexical chunks at the bi-mora level contribute to the representation of novel sequences in short-term memory.

Experiment 2 investigated the boundary condition of bi-element frequency effects. We inserted two 1-s pauses in each memory list to temporally divide the bi-morae, causing online temporal grouping to conflict with long-term phonotactic chunking. The results showed that pauses significantly diminished the backward association frequency effect. This suggests that appropriate (prosody-based) segmentation is a basis for the recognition of phonotactically-defined chunks, which underlie the contribution of long-term knowledge to short-term serial order memory.

In contrast, the presence of temporal pauses did not eliminate the forward association effect, indicating the greater strength of forward association than of backward associations. This asymmetric robustness of association frequency effects suggests that the bi-element frequency effect cannot be attributed only to the recognition of frequent bi-element chunks, which is assumed to occur at encoding. Bi-element associations were separated and disrupted during encoding/recognition by temporal pauses in Experiment 2 of the present study. The remaining forward association frequency effects, therefore, would possibly arise after the recognition process of the memory sequence. There might be some processing stages that benefit only from forward association. Speech production at recall could be such a processing stage. For example, Sevald and Dell (1994) proposed a sequential cueing mechanism where a phoneme cues next phonemes via chunk representations. That is, they assumed that phonemes are activated sequentially in speech production. In such a mechanism, the forward association frequency (but not backward association frequency) positively affects recall performance. Sequential cueing or similar production mechanisms (e.g., associative forward chaining) might underlie the bi-element frequency effect on short-term serial order memory.

We noticed, however, a subtle pattern in the data related to the null influence of pauses on forward association frequency: despite the lack of any significant interaction, the seventh mora showed attenuation of the forward association frequency effect with anterior

pause, as seen in Figure 3 (recall the decrement of the mora in dextral sequences to the same level as the mora in low-frequency sequences). Therefore, forward association frequency might be sensitive to the presence of pauses to some extent, depending on serial positions. Our current design might not be powerful enough to detect such subtle effect. An issue to be addressed in the future is whether and how forward association overcomes temporal pause in the fourth position and why it attenuates in seventh position in the sequences.

Finally, we discuss the interaction between segmentation based on long-term bi-element chunking and perceptual cues on speech recognition. As we have already discussed, one possible explanation of the bi-mora frequency effect is based on the assumption that long-term representations of high-frequency bi-elements enable us to segment and recognise those bi-elements within whole sequences. Some serial order memory models (e.g., Burgess & Hitch, 2006; Page & Norris, 2009) explicitly assume a mechanism in which a previously encountered chunk is first recognised and then used to reproduce the entire sequence that contains it. On the one hand, the long term memory-based chunking/recognition of coming sequences is assumed to contribute to the detection of coherent (that is, previously encountered) units even in processes of statistical learning/word segmentation from a speech stream without pauses (e.g., Saffran et al., 1996; Giroux & Rey, 2009; see also Plaut & Vande Velde, 2017). On the other hand, the pauses provide effective cues for segmentation of speech and can more strongly mark unit boundaries than long-term representations of bi-elements can. Indeed, Finn and Kam (2008) showed that when sound units segmentable by already learned phonotactics conflict with segmentation of novel, to-be-learned units, learning of the new units is not efficient; however, the interference of phonotactic knowledge was weakened by the presence of temporal pauses at the boundaries of the to-be-learned units. This again indicates the greater effect of temporal cues vs. phonotactics cues on speech segmentation. Furthermore, speech segmentation is achieved not only by temporal pauses but also by other

prosodic cues, such as preboundary vowel lengthening and pitch change (e.g., Johnson & Seidl, 2008; Seidl, 2007; Seidl & Cristià, 2008; Wellmann, Holzgrefe, Truckenbrodt, Wartenburger, & Höhle, 2012). These prosodic aspects can provide potential cues for segmentation that operate in short-term serial order memory (e.g., Frankish, 1996).

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Figure captions

Figure 1. Examples of the sequence composition. Circles represent each mora. Low frequency associations between morae are depicted in thin dashed lines, and high frequency associations are depicted in heavy solid lines. Two vertical solid lines represent the position of the 1-s temporal pauses. In this example, the low-frequency sequence 'me-to-hi-zo-wa-ho-ge-pu-ke' was made first for the seed sequence, where all bi-morae were of low frequency. Then, the seed sequence was slid forward and the ninth mora 'ke' was moved to the head of the sequence to make the dextral sequence, where the first bi-mora 'ke-me' also had a low level of frequency. The seed sequence was also slid backward and the first mora 'me' was moved to the last position to make the sinistral sequence. Mixed-frequency sequences were generated using the same method of sliding, except all bi-morae were of high frequency other than the third and sixth ('yo-hi' and 're-ba,' respectively, in this example) which were of low frequency. The bi-mora composed of the ninth ('go') and first ('ze') morae in the seed sequences were high frequency. Sequence sliding allowed the positions of low frequency bi-morae to be moved in each direction, as depicted.

Figure 2. Rates of recall accuracy for morae on each serial position in mixed-frequency sequences and low-frequency sequences in Experiment 1 without temporal pauses. For mixed-frequency sequences, recall rates were averaged for each of the seed, dextral, and sinistral sequences. On the other hand, recall rates were averaged across the three sequence types for low-frequency sequences because there were no variations of bi-mora frequency across all serial positions in low-frequency sequences. Frequent associations are depicted in solid lines. Morae concatenated with low frequent associations are not connected with lines. Error bars represent *SE*.

Figure 3. Rates of recall accuracy for morae on each serial position in mixed-frequency sequences and low-frequency sequences in Experiments 2, in which 1-s temporal pauses were inserted between third and fourth morae and between sixth and seventh morae. The way of figure depiction is the same as that in Figure 2.
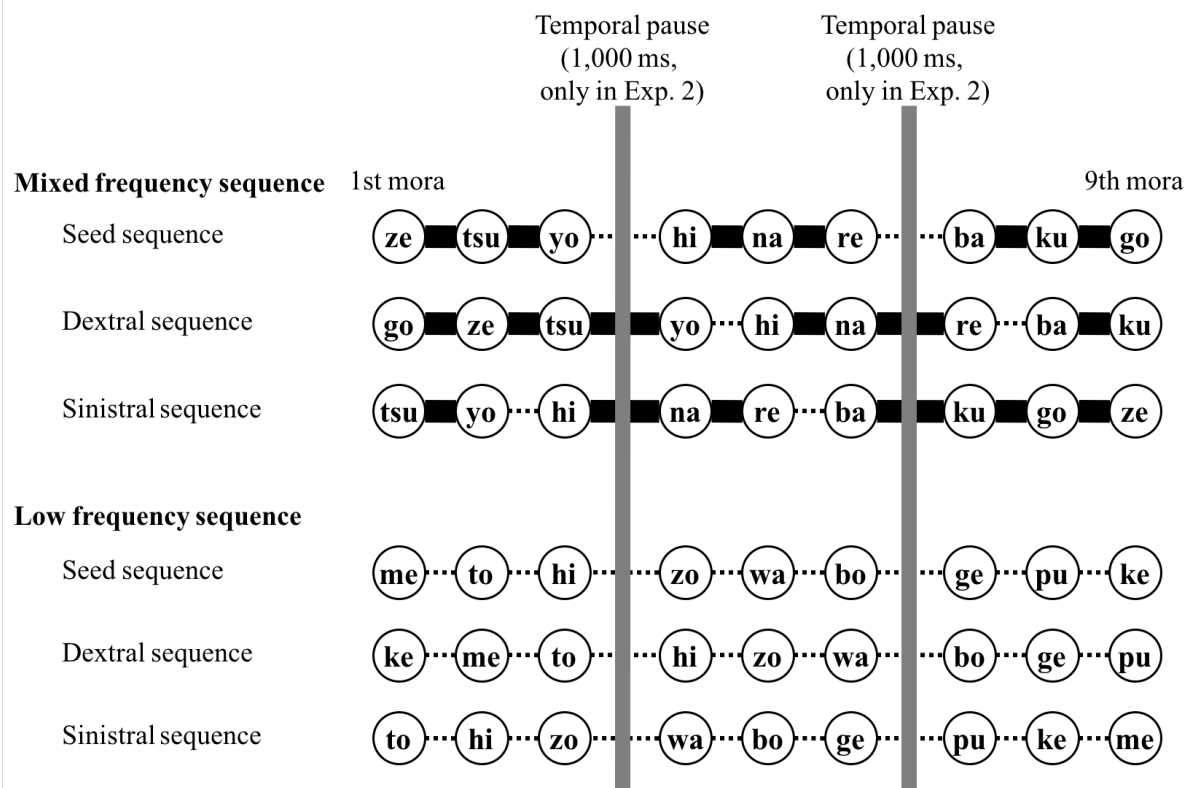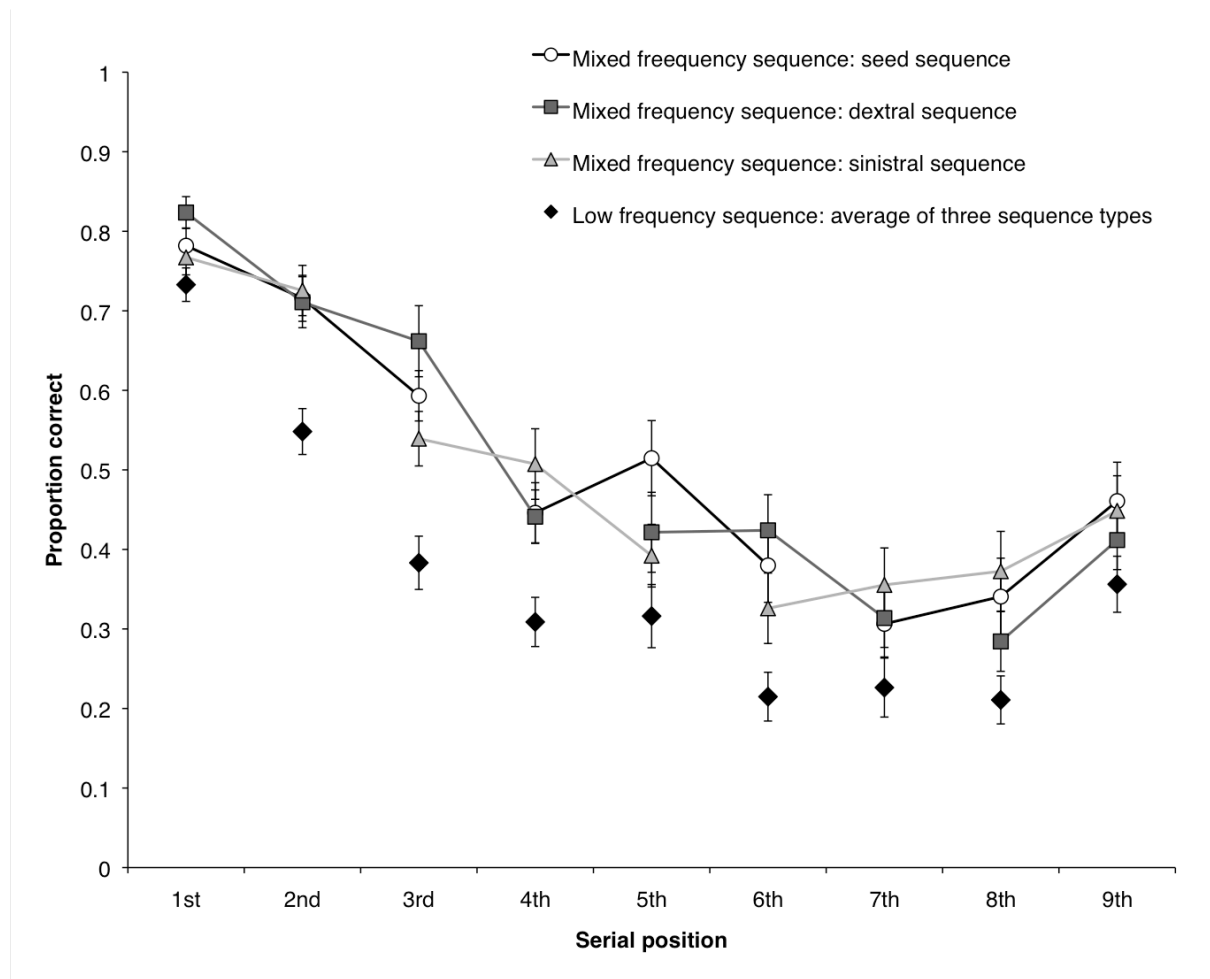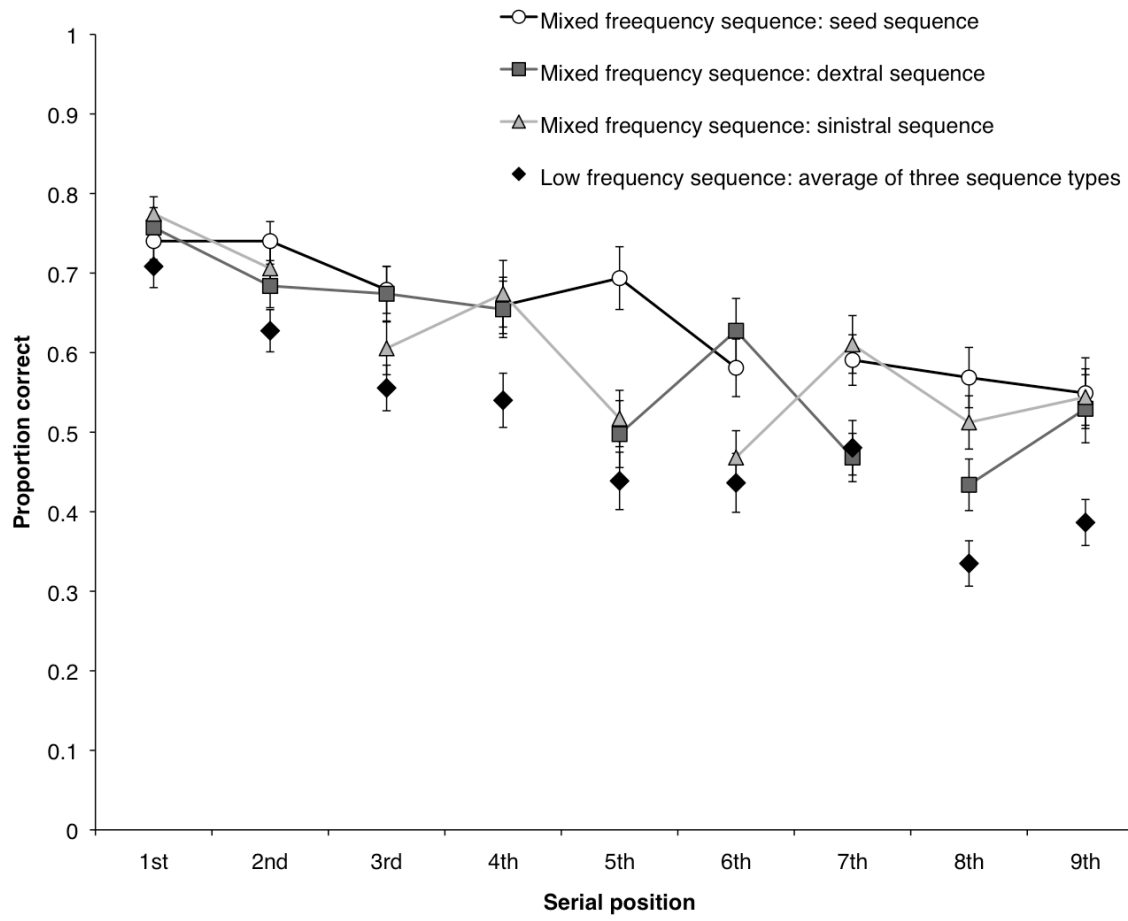
Figure 1

Figure 2

Figure 3

Tables

Table 1. Properties of token frequency of bi-morae employed in mixed-frequency sequences and low-frequency sequences

	mixed-frequency sequence				low-frequency sequence			
	M	SD	max	min	M	SD	max	min
High frequent bi-mora	92989.29	110072.66	1061925	25058	-	-	-	-
Low frequent bi-mora	751.43	667.43	2483	0	618.76	685.96	2480	0

Note. There were no high frequent bi-morae in low-frequency sequences.

Table 2. Outcomes of mixed effect logistic regression analysis in Experiment 1

	Estimate	*SE*	*z value*	*p*	*χ2*	*p*
Intercept	-0.65	0.29	-2.23	0.03		
Forward association frequency	0.24	0.08	3.19	< .01	9.98	< .01*
Backward association frequency	0.15	0.07	2.08	0.04	4.16	0.04*

*p < .05.

Table 3. Outcomes of mixed effect logistic regression analysis on the random intercept only model in Experiment 2.

	Estimate	SF	z value	p	χ2	p
Intercept	0.19	0.22	0.87	0.39		
Forward association frequency	0.19	0.05	3.56	< .01	12.66	< .01*
Backward association frequency	0.12	0.05	2.34	0.02	5.47	0.02*
Anterior pause	0.19	0.33	0.60	0.55	0.35	0.56
Posterior pause	0.18	0.33	0.55	0.58	0.30	0.59
Interaction: forward association frequency and anterior pause	-0.16	0.10	-1.58	0.11	2.51	0.11
Interaction: forward association frequency and posterior pause	-0.04	0.10	-0.35	0.72	0.13	0.72
Interaction: backward association frequency and anterior pause	0.06	0.10	0.61	0.55	0.37	0.55
Interaction: backward association frequency and posterior pause	-0.21	0.10	-2.10	0.04	4.42	0.04*

* $p < .05$.

Appendix A

Table A. Seed sequences of mixed- and low-frequency sequences

mixed-frequency sequences		
bu-ri-yo-de-ha-ge-zi-ta-no	*ma-ku-ze-ba-tsu-ga-fu-shi-ru*	*su-ki-bo-hi-da-re-mi-to-na*
chi-yo-ne-ro-su-de-wa-ko-zi	*ma-ne-tsu-pa-ri-ga-ho-ku-za*	*su-ta-yo-zu-ka-bu-ni-wa-me*
fu-ki-se-zi-me-gu-yo-bi-ru	*mi-ga-re-bu-ki-yu-zi-da-shi*	*ta-ko-ba-ge-shi-me-fu-do-ri*
ga-ke-to-ne-ra-be-mi-se-da	*mi-su-be-gu-chi-ra-hi-ku-zi*	*ta-ku-ne-zo-re-ba-mi-sa-hi*
gi-se-ma-be-ki-te-hi-de-ru	*mu-ri-te-fu-so-ba-zo-ne-ku*	*ta-shi-bo-ga-no-mu-hi-ko-re*
gi-wa-ru-pe-ki-do-bu-mo-tsu	*na-tsu-re-gu-mi-da-zu-ki-sa*	*te-ra-so-de-ki-zu-go-ya-me*
gu-ta-be-hi-ka-ne-wa-su-ma	*na-zi-sa-fu-ta-bi-gu-ri-ku*	*te-shi-ge-ni-yo-mi-bo-ku-hi*
ha-ke-na-pu-re-zo-da-su-te	*ne-ru-do-ya-mu-chi-za-su-ke*	*to-ka-ni-fu-mi-zu-so-da-ri*
ha-zi-do-wa-ri-yu-shi-te-ku	*ni-ta-mu-wa-ku-gi-ba-su-zi*	*to-ki-ne-yo-bu-re-so-fu-ma*
ka-zu-re-nu-shi-do-ge-tsu-bi	*ra-ni-ga-be-tsu-ze-mu-ki-su*	*to-ma-ke-gi-no-de-zu-shi-ho*
ke-shi-ha-ni-to-bi-zu-ra-mu	*ra-shi-ze-ya-to-ha-mi-na-do*	*to-ni-ho-de-mo-wa-ro-se-ka*
ke-tsu-ya-re-na-ge-do-ma-zu	*ra-zi-yu-ho-te-ga-bu-ka-mo*	*to-re-da-ho-ka-yo-zi-mo-na*
ki-ro-zi-de-su-me-chi-na-go	*re-ka-te-bo-ne-da-zo-mu-shi*	*tsu-ba-re-yo-mu-ne-do-ki-so*
ko-su-po-ge-ru-ba-mo-ni-tsu	*re-ma-do-tsu-no-bi-fu-zi-ke*	*tsu-ra-bu-no-ma-de-ko-ha-zu*
ku-da-me-ho-shi-yo-pa-tsu-na	*ro-ku-ge-ya-bu-wa-so-chi-da*	*yo-ku-ho-bu-ta-zu-de-ni-mo*
ku-do-ru-yo-sa-mi-fu-to-zu	*shi-ko-za-de-na-be-ro-ga-tsu*	*ze-tsu-yo-hi-na-re-pa-ku-go*
ku-te-ho-ya-shi-bu-gi-mo-ru	*so-re-wa-yo-te-mi-de-ba-ku*	*zi-ko-da-fu-ra-bi-te-mo-shi*

low-frequency sequences		
me-to-hi-zo-wa-bo-ge-pu-ke	*ke-ya-be-za-ne-go-pu-sa-de*	*sa-pu-hi-nu-me-ro-be-gi-do*
bu-pe-za-re-gi-so-ta-he-yu	*ku-po-bi-so-nu-mi-he-za-gu*	*se-bo-mu-no-pa-zo-ga-yu-he*
da-so-pe-yo-re-zu-he-to-nu	*me-hi-pu-de-ro-nu-ba-yo-za*	*se-no-yu-po-mu-he-zi-gu-de*
de-fu-gi-pe-so-ze-bu-te-nu	*na-bo-pe-fu-ge-to-yu-ro-ze*	*shi-he-pu-ni-mu-ya-bi-zo-gu*
do-pe-ho-ni-bo-yu-ze-go-se	*na-pi-re-bo-te-za-yo-ga-he*	*so-pi-bo-ze-ri-ho-mi-nu-go*
do-pi-nu-ro-ha-yo-ze-gi-be	*ne-ya-bo-mi-pu-ge-zu-ro-he*	*wa-po-gi-zu-ho-nu-so-mi-be*
ga-pe-ya-ze-bi-me-wa-ho-re	*ni-pu-ki-he-mu-do-bi-re-ya*	*ya-go-he-ka-pu-do-nu-wa-be*
ga-pu-ma-zo-sa-bo-de-nu-ho	*ni-ze-wa-pi-ho-ba-yu-ge-mu*	*ya-hi-pa-nu-ta-so-wa-ge-bo*
go-chi-de-so-pa-fu-be-mu-zo	*ni-zo-ri-pa-mo-ge-hi-su-bo*	*yo-pu-se-mu-ba-gi-ze-ha-ro*
gu-be-no-tsu-pi-da-ze-yo-fu	*pa-hi-bu-zo-shi-ne-chi-yu-gi*	*yu-no-ge-ho-pu-be-zo-chi-so*
gu-hi-pe-ba-nu-yo-ra-ze-da	*pa-mi-yu-hi-gu-zo-bi-ke-chi*	*za-bi-po-nu-se-ya-he-mi-ge*

gu-to-pa-zu-do-yu-se-ho-mu	pa-yu-chi-he-bi-go-zu-wa-do	za-mo-hi-po-ra-bo-gu-ya-nu
ho-ma-pu-yo-be-zu-ge-sa-ro	pe-ko-ze-bo-ma-he-ga-de-sa	zi-yo-pi-ra-he-gi-me-so-be
ka-pe-mu-be-yu-wa-tsu-he-gu	pe-ni-te-gi-he-mo-za-yu-be	zo-be-sa-po-ya-ho-gu-me-nu
ke-ba-ze-pu-da-go-na-so-he	pi-so-ha-bo-za-ge-mi-ro-chi	zo-ha-pe-ri-bo-se-ni-de-go
ke-pa-bi-ze-sa-mo-he-yo-ge	re-po-ba-go-de-zo-nu-sa-he	zo-pu-ka-he-ni-re-go-yu-do
ke-ri-he-pi-zu-ga-nu-bo-me	re-za-chi-pu-he-bu-me-gi-de	zo-su-he-go-pi-me-na-yu-ko

Appendix B

Table B. Abbreviations in formulae

abbreviation	
correctness	correctness of mora recall
FAF	forward association frequency
BAF	backward association frequency
AP	presence of anterior pause
PP	presence of posterior pause
FAF:AP	interaction between forward association frequency and presence of anterior pause
FAF:PP	interaction between forward association frequency and presence of posterior pause
BAF:AP	interaction between backward association frequency and presence of anterior pause
BAF:PP	interaction between backward association frequency and presence of posterior pause
participant	participant ID
sequence	stimulus sequence ID
position	serial position

Formula 1: glmer (correctness ~ 1 + FAF + BAF + (1 + FAF + BAF | participant) + (1 + FAF + BAF | sequence) + (1 + FAF + BAF | position), family = binomial(link=logit), control = glmerControl(optCtrl = list(maxfun = 1e6)))

Formula 2: glmer (correctness ~ 1 + FAF + BAF + (1 + FAF + BAF | participant) + (1 + FAF + BAF | sequence) + (1 | position), family = binomial(link=logit), control = glmerControl(optCtrl = list(maxfun = 1e6)))

Formula 3: glmer (correctness ~ 1 + FAF + BAF + AP + PP + FAF:AP + FAF:PP + BAF:AP + BAF:PP + (1 | participant) + (1 | sequence) + (1 | position), family = binomial(link=logit), control = glmerControl(optCtrl = list(maxfun = 1e6)))

Appendix C

Table C. Outcomes of a model to assess the fixed effect of interaction between backward association frequency and presence of posterior pause while considering the influence of a random slope of the interaction.

	Estimate	SE	z value	p	χ2	p
Intercept	0.19	0.22	0.87	.38	-	-
Forward association frequency	0.19	0.05	3.56	< .01*	-	-
Backward association frequency	0.12	0.05	2.35	.02*	-	-
Anterior pause	0.20	0.33	0.60	.55	-	-
Posterior pause	0.18	0.33	0.56	.58	-	-
Interaction between forward association frequency and anterior pause	-0.16	0.10	-1.58	.11	-	-
Interaction between forward association frequency and posterior pause	-0.04	0.10	-0.38	.70	-	-
Interaction between backward association frequency and anterior pause	0.06	0.10	0.61	.54	-	-
Interaction between backward association frequency and posterior pause	-0.21	0.12	-1.75	.08+	3.02	.08+

* $p < .05$, + $p < .10$.

The formula in the format for lme4 was "glmer (correctness ~ 1 + FAF + BAF + AP + PP + FAF:AP + FAF:PP + BAF:AP + BAF:PP + (1 + BAF:PP | participant) + (1 + BAF:PP | sequence) + (1 | position), family = binomial(link=logit), control = glmerControl(optCtrl = list(maxfun = 1e6)))." Table B provides explanation of abbreviations. A morel with the random slope for serial position did not converge because of high correlation between the random intercept and the random slope for serial position. Therefore we employed the model dropping the random slope.