Speech segmentation and cross-situational word learning in parallel

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Abstract

Language learners track conditional probabilities to find words in continuous speech and to map words and objects across ambiguous contexts. It remains unclear, however, whether learners can leverage the structure of the linguistic input to do both tasks at the same time and how that would impact learning. To explore these questions, we combined speech segmentation and cross-situational word learning into a single task. Participants had to track speech statistics (transitional and phonotactic probabilities) to segment words and, at the same time, track co-occurrences between these newly segmented words and objects across presentations to overcome ambiguity and learn word-object pairings. In Experiment 1, when adults (N = 60) simultaneously segmented continuous speech and mapped the newly segmented words to objects, they demonstrated better performance than when either task was performed alone. However, when the speech stream had conflicting information between transitional and phonotactic statistics, participants were still able to correctly map words to objects, but surprisingly, were at chance level on speech segmentation. In Experiment 2, we used a more sensitive speech segmentation measure to find that adults (N = 35), exposed to the same conflicting speech stream, correctly identified non-words as such, but were still unable to consistently discriminate between words and part-words. Again, mapping was above chance. Our study suggests that learners can track multiple sources of statistical information to find and map words to objects in complex environments. It also prompts critical questions on how to effectively measure the knowledge that may arise from these learning experiences.

Keywords. Statistical learning, speech segmentation, cross-situational word learning, word learning

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Language learners master several complex tasks. For instance, they discover words from continuous speech and map them to referents across ambiguous situations. The present study explores how tracking conditional probabilities in audiovisual input may help learners to solve both tasks simultaneously. We combine two well established statistical learning tasks—speech segmentation (e.g., Romberg & Saffran, 2010; Saffran et al., 1996) and cross-situational word learning (e.g., Smith & Yu, 2008; Yu & Smith, 2007)—into a single paradigm.

Faced with continuous speech and only a few words in isolation (~10%, Brent & Siskind, 2001), one of the crucial challenges for language learners is to segment streams of words into discrete units. Conditional probabilities between syllables (i.e., transitional probabilities; Krogh et al., 2013; Romberg & Saffran, 2010; Saffran et al., 1996) provide one cue that aids segmentation (for evidence of other cues, see Hay & Saffran, 2012; Johnson et al., 2014). In natural speech, syllables that form words tend to have higher likelihood of co-occurrence (higher Transitional Probabilities, TPs) in comparison to syllables across word boundaries (Swingley, 1999; but see Yang, 2004), which provides a potential cue to segmentation. There is now a vast empirical literature showing that language learners can track differences in TPs across syllable sequences to segment continuous speech into discrete words (for reviews see Cannistraci et al., 2019; Cunillera & Guilera, 2018; but see Black & Bergmann, 2017). The experimental task in these studies usually start by familiarizing participants with a continuous speech stream in which TP is the only cue to word boundaries. For instance, some syllables *always* occur together (creating a word), *sometimes* occur together (creating a part-word or a low TP word), or *never* occur together (creating a non-word). Following familiarization, participants' preferences for words, part-words, or non-words are measured. By and large participants differentiate words from foils (part-words or non-words), suggesting

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that they successfully tracked TP information to find words in the continuous speech stream.

Assigning meaning to words is another challenge for language learners. There is evidence that, early in development, recently segmented words (with stronger TPs) are treated as better candidate labels on subsequent mapping tasks (Estes et al., 2007; Hay et al., 2011). While the benefit of high TP sequences during word learning appears to diminish across development (Karaman et al., 2022; Mirman et al., 2008; Shoaib et al., 2018), learners continue to be remarkably successful both at segmenting speech using TP information (Saffran et al., 1996) and at making one-to-one mappings between labels and referents (Estes, 2009; Estes et al., 2007; Lany & Saffran, 2010). In everyday life, however, several words are presented with several potential referents at the same time, creating ambiguous learning experiences (Quine, 1960). A growing empirical literature shows that learners can track word-object co-occurrences across ambiguous situations to find the meaning of words (for a recent meta-analysis, see Dal Ben et al., 2019; but see Smith et al., 2014). The experimental task in these studies usually familiarize participants with a series of ambiguous trials. On each trial, two (or more) words are presented with two (or more) objects. On any given trial, there is insufficient information to solve the ambiguity. However, if participants compare word-object conditional probabilities across trials, specific word-object relations can be learned[1] (Smith & Yu, 2008; Yu & Smith, 2007).

The evidence that conditional probabilities can promote both segmentation and cross-situational word learning prompts the question of whether these processes unfold in sequence or in parallel. Related evidence for the latter is reported by Cunillera, Laine,

[1] Here we do not join the productive debate between hypothesis-testing and aggregation as learning mechanisms for cross-situational word learning (e.g., Yurovsky & Frank, 2015), as we believe it is beyond the scope of our study.

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and colleagues (2010). Adults were familiarized with a continuous speech stream and, at the same time, with a stream of objects. When the first word was being played, its corresponding object was displayed on the screen; when the second word started, its corresponding object replaced the previous one, and so forth. From this dynamic presentation, participants were able to segment words from the continuous speech and to map them to its corresponding objects in parallel. In addition, in a follow-up study, François and colleagues (2017) replicated the findings and showed neurophysiological markers for online simultaneous speech segmentation and mapping. Together, these studies show that segmentation and mapping can happen in parallel–see also Shukla and colleagues (2011) and Thiessen (2010) for a related task with infants. However, for all these studies, the word learning task was not ambiguous.

Intuitively, adding mapping ambiguity could make the simultaneous task too challenging. However, Räsänen and Rasilo (2015) proposed just the opposite. In a comprehensive combination of computational simulations and reanalyzes of empirical data, the authors argue that tracking cross-modal conditional probabilities between words and objects in ambiguous situations may boost both speech perception and word learning, in comparison to tracking only TPs or word-object co-occurrences. This is in line with recent meta-analytic findings showing that infants effectively integrate audio and visual information, from a variety of sources, when learning language (e.g., Cox et al., 2022).

Here we explore this idea empirically. Our study is guided by two main questions. First, we ask whether words can be segmented and mapped at the same time across ambiguous presentations. To answer this question, we adapted the design by Cunillera, Laine, and colleagues (2010) to combine a speech stream with several new objects in an ambiguous fashion. Second, we ask whether the joint task would improve

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segmentation and mapping in comparison to separate tasks. To answer this second question, we compared the performance from the present study with the performance from previous research that tested speech segmentation (Dal Ben et al., 2021) and cross-situational word learning (Dal Ben et al., 2022) separately, but using the same stimuli and population.

Moreover, previous studies (Dal Ben et al., 2021, 2022) also investigated the combined effects of conditional probabilities and phonotactics on both speech segmentation and cross-situational word learning. Phonotactic probability (PP) was defined as the conditional probability of a syllable occurring in a given position of a word from a given language (Vitevitch & Luce, 2004). Whereas Dal Ben and colleagues (2021) found a boost in segmentation when phonotactics and TPs worked together to signal word boundaries, segmentation was impaired when phonotactics and TPs were in conflict (see also Finn & Hudson Kam, 2008; Mersad & Nazzi, 2011). Dal Ben and colleagues (2022) did not report any evidence for phonotactic interference during the cross-situational word learning task.

Given the importance of phonotactics to speech perception and word learning (Benitez & Saffran, 2021; Sundara et al., 2022), our present study also asks whether differences in phonotactics would impact speech segmentation and cross-situational word learning in parallel. By adding this question and using the same stimuli and population, we more directly compare our present study with previous research. Moreover, we advance our understanding of how multiple linguistic statistics can be combined when learning novel words across ambiguous situations (Saffran, 2020; Smith et al., 2018).

Experiment 1

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To investigate whether words can be segmented and mapped simultaneously and whether differences in phonotactics would impact this joint performance, we exposed participants to continuous speech streams with varying distributions of phonotactics and TPs. At the same time, we also presented them with a series of objects, two at a time, that corresponded to the words in the speech streams. Critically, one of the languages had TPs and phonotactics aligned, consistently pointing to word boundaries. In another language, words and part-words had balanced phonotactics, with TPs being the only informative statistic to word boundaries. In a third language, TPs and phonotactics were in conflict: TPs pointed to word boundaries and phonotactic information pointed to syllables within-words (part-words).

To investigate whether the joint task would improve segmentation and mapping in comparison to separate tasks, we compared segmentation and mapping performance in the present combined task with performance in the individual tasks (i.e., speech segmentation only and cross-situational word learning only; Dal Ben et al., 2021, 2022, respectively).

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Method

Participants

Sixty native Brazilian-Portuguese-speaking adults (M_{age} = 21.37 years, ± 3.27 *SD*, 32 female) participated. None of the participants reported any visual or auditory impairments that could interfere with the task. Participants were recruited online at the official Facebook group of [ANONYMIZED], where data was collected. They received no compensation for their in-person participation. The study was conducted according to the Declaration of Helsinki and the Ethics Committee of the host university approved the research (#1.484.847). Participants were randomly assigned to one of three groups.

Stimuli and Design

Auditory Stimuli. Three frequency-balanced languages from Dal Ben and colleagues (2021) were used (see Table 1). Each language contained six statistically defined disyllabic pseudo-words (TP = 1), which served as labels in our task. Test words and part-words in all Languages were frequency balanced (Aslin et al., 1998). In each language, half of the words were repeated 300 times (labeled H on Table 1) and the other half were repeated 150 times (labeled L on Table 1). The recombination of syllables from the words with higher frequency generated three part-words, used during test, that had lower TPs (TP = 0.5), but that were balanced in frequency with the test words (150 repetitions each; Aslin et al., 1998).

In addition, all words and part-words had legal phonotactics in Brazilian-Portuguese. However, some had higher phonotactic probability than others (Table 1, PP+ or PP-). Phonotactics were calculated using Vitevitch and Luce's (2004) algorithm and Estivalet and Meunier (2015) database of Brazilian-Portuguese biphones. Briefly, we divided the sum of the log (base 10) of token frequency of each biphone on each word position by the total log frequency of words with biphones in that given position (e.g., /mæ/ in the third biphone divided by the total log frequency of all words with at least three biphones). Then, using a custom search engine, we created six novel disyllabic words with consonant–vowel structure (CVCV) and with the highest possible phonotactic probability before becoming actual words in Brazilian-Portuguese (labeled PP+; Table 1). Lastly, we recombined their biphones to create other six novel words that had slightly less probable, but still high, phonotactic probabilities (labeled PP−; Table 1). For a full description of the phonotactic calculations, see Dal Ben and colleagues (2021) and Vitevitch and Luce (2004).

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Languages were synthesized using the MBROLA speech synthesizer with a Portuguese female voice[2] (Dutoit et al., 1996). Prosodic cues were minimized by setting the pitch constant at 180 Hz, the intensity at 77 dB, and the duration of each word to 696 ms (cf. Cunillera, Laine, et al., 2010). The total duration of each language was 15 min 39 s and 424 ms.

Table 1

Words and Part-words (grapheme and IPA) and their Phonotactic Probabilities (PP+ or PP-) and Frequency (High or Low) for the Balanced, and Aligned, Conflict Languages

Language	Familiarization				Test							
	Words		**PP**	**Freq**	**Words**		**PP**	**TP**	**Part-words**		**PP**	**TP**
Balanced	sute	[sute]	H+	H	nipe	[nipe]	H-	1.0	teba	[teba]	H-	0.5
	viko	[viko]	H+	H	tadi	[tad͡ʒi]	H-	1.0	kosu	[kosu]	H-	0.5
	bara	[baʁa]	H+	H	mide	[mide]	H-	1.0	ravi	[ʁavi]	H-	0.5
	nipe	[nipe]	H-	L								
	tadi	[tad͡ʒi]	H-	L								
	mide	[mide]	H-	L								
Aligned	dini	[d͡ʒini]	H+	H	sute	[sute]	H+	1.0	nipe	[nipe]	H-	0.5
	deta	[deta]	H+	H	viko	[viko]	H+	1.0	tadi	[tad͡ʒi]	H-	0.5
	pemi	[pemi]	H+	H	bara	[baʁa]	H+	1.0	mide	[mide]	H-	0.5
	sute	[sute]	H+	L								
	viko	[viko]	H+	L								
	bara	[baʁa]	H+	L								
Conflict	teba	[teba]	H-	H	nipe	[nipe]	H-	1.0	sute	[sute]	H+	0.5
	kosu	[kosu]	H-	H	tadi	[tad͡ʒi]	H-	1.0	viko	[viko]	H+	0.5
	ravi	[ʁavi]	H-	H	mide	[mide]	H-	1.0	bara	[baʁa]	H+	0.5
	nipe	[nipe]	H-	L								
	tadi	[tad͡ʒi]	H-	L								
	mide	[mide]	H-	L								

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[2] We used the MBROLA database br4 (available at: https://github.com/numediart/MBROLA-voices).

Following our previous studies, TPs and phonotactics were combined to create three languages. The Balanced language had test words (TP = 1.0) and part-words (TP = 0.5) with balanced phonotactic probabilities (M_{words} = 0.0072, $M_{part\text{-}words}$ = 0.0075; Table 1); this language served as a control. The Aligned language had test words with higher phonotactic probabilities in comparison to part-words (M_{words} = 0.0085, $M_{part\text{-}words}$ = 0.0072; Table 1). Thus, both TPs and phonotactics signaled word boundaries. Finally, in the Conflict language: test words had lower phonotactic probabilities in comparison to part-words (M_{words} = 0.0072, $M_{part\text{-}words}$ = 0.0085; Table 1). Thus, TPs highlighted word boundaries whereas phonotactics highlighted part-words.

Visual stimuli. Six novel objects, used by Dal Ben and colleagues (2021), were also used in the present experiment. They were realistic, colorful, 3D objects that are part of the NOUN object base (Horst & Hout, 2016) and were chosen based on their high degree of novelty (*M* = 77%) and discriminability (*M* = 90%). For each language, objects and words were randomly paired, forming six word-object pairs. All stimuli are openly available at https://osf.io/rs2bm/?view_only=95970ffcb2c9402aa77f3bc4b193abbb [anonymized for peer-review].

Design. Our paradigm (Figure 1) was an adaptation of Cunillera, Laine, and colleagues (2010) and combined speech segmentation and cross-situational word learning in the same task. It had two phases: familiarization and test. During familiarization, one of the languages (Balanced, Aligned, Conflict) was played while objects were displayed on the computer screen. We matched words from the speech stream and objects on the screen in such a way that, at any given time, two objects were displayed while their corresponding words were presented (≅ 1392 ms; Figure 1). For instance, when the first word was first presented, the objects corresponding to the first

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and second words were displayed; when the third word was played, the first two objects were replaced by two other objects and so on. This created a highly dynamic adaptation of the classic 2 x 2 cross-situational word learning arrangement (for a video sample, see https://osf.io/rs2bm/?view_only=95970ffcb2c9402aa77f3bc4b193abbb; cf. Smith & Yu, 2008). Importantly, the onset and offset of the words and objects were desynchronized (± 100, ± 150, or ± 200 ms) to avoid additional cues to speech segmentation (Cunillera, Càmara, et al., 2010). In addition, the entire audio stream had a fade-in and fade-out effect of 500 ms to minimize cues for the initial and final words' boundaries. Finally, to minimize fatigue from this extensive exposure (a total of 1350 word-object presentations, or 675 2x2 "trials", over ≅ 15 minutes), we divided the familiarization into five blocks. Each block had 90 word-object presentations—20 for the high frequency word-object pairs and 10 for the low frequency pairs—and lasted a little over 3 minutes. Between blocks, participants were given a 5-second pause on a screen displaying the task progress (e.g., "Block 2 of 5").

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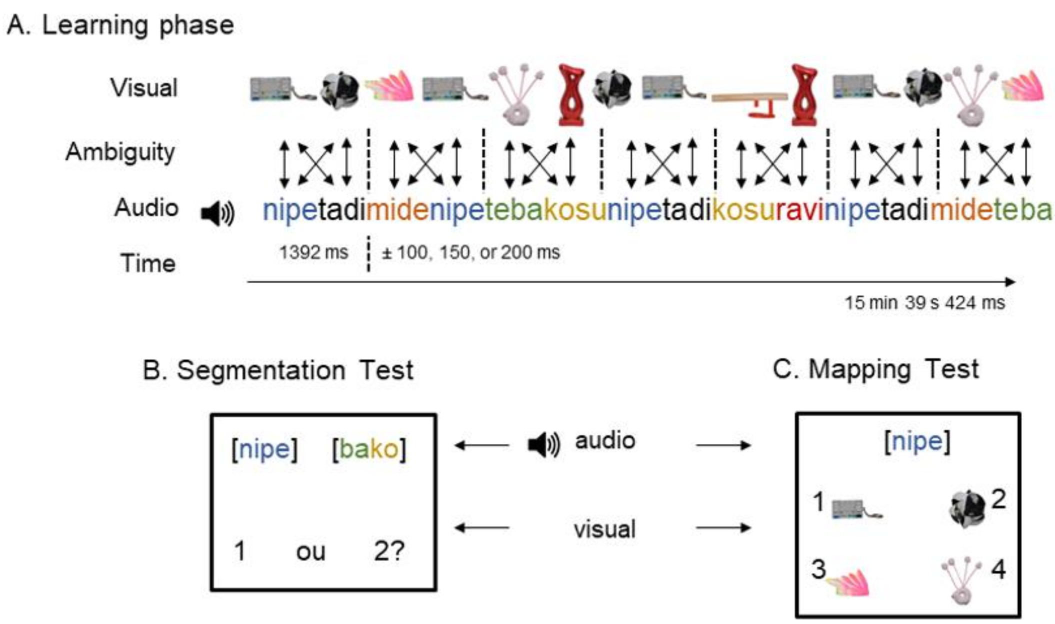

Figure 1. Panel A displays the Familiarization phase, with dynamic trials combining the continuous speech stream with two objects at a time. Panel B displays a trial of the speech segmentation test (two-alternative forced-choice). Panel C displays a trial of the mapping test (four-alternative forced-choice).

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Following familiarization, two tests were performed, always in the same order: segmentation and mapping. The segmentation test followed a two-alternative forced-choice structure. On each trial, a frequency-balanced word (i.e., a low frequency word, TP = 1, 150 repetitions) and a part-word (TP = 0.5, 150 repetitions) were played with a pause of 500 ms between them. Participants were prompted to indicate which one was a word from the speech stream they had just heard. The order of presentation of words and part-words was counterbalanced across trials. Each of the three low frequency words were tested six times across 18 test trials.

The mapping test followed a four-alternative forced-choice structure. Each trial began with four objects displayed in the corners of the screen: one target object (co-occurrence probability = 1 with target word) and three distractors (co-occurrence probability = 0.2 with target word). After 1 second, a target word was played and participants were prompted to select the matching object. Each of the 6 word-object pairs (3 high frequency words and 3 low frequency words) were tested twice across 12 trials.

Procedure

The experiment was conducted in a sound-attenuated room and was computer administered using Psychopy2 (Peirce et al., 2019). Auditory stimuli were played on high-definition neutral headphones (AKG K240 powered by Fiio e10K dac/amp). All responses were entered on an adapted numeric keyboard with only the keys: 1, 2, 3, 4, Return, +, and - (to increase or decrease the audio volume). At the beginning of the experiment, music with the same intensity as the experimental stimuli (77 dB) was played and participants were instructed to adjust the volume to a comfortable level.

Next, they were instructed that they would hear a new language and see new objects and that their task was to discover which words corresponded to which objects. Following familiarization, they were tested on segmentation and mapping. The first two trials of each testing phase were warm-up trials used to familiarize participants with the structure of the tasks. For example, before the segmentation test trials began, participants were presented with two practice trials with a common word from Brazilian-Portuguese versus a nonsense word (e.g., pato [duck] vs. tafi). Similarly, before the mapping test trials began, participants were presented with two practice trials during which they heard a familiar word and were presented with 4 familiar objects (e.g., “pato” + picture of a duck, house, cat, ball). In addition, after each test phase, participants were asked to estimate their performance by indicating if the percentage of correct responses was between 0 - 25%, 25 - 50%, 50 - 75%, or 75 - 100%. Participants’ compliance to instructions was continuously assessed using a CCTV system. At the end, participants answered a questionnaire about their educational background and language abilities.

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Data Analysis

After excluding inattentive responses, defined as test trials with reaction times greater than 3 SDs away from the mean (segmentation: 15 trials, 1% of the data; mapping: 17 trials, 2% of the data), we fitted mixed-effects logistic regressions using the lme4 package for R (Bates et al., 2015; R Core Team, 2021) and Spearmans' correlations, also in R, to explore speech segmentation performance, cross-situational word learning performance, relationships between them, and self-evaluation. Specific models, outcomes, and predictors are described in the next section. Given the exploratory nature of our investigation, we report effect size estimations and confidence intervals, but not *p*-values (Scheel et al., 2020). All scripts and data are openly available at https://osf.io/rs2bm/?view_only=95970ffcb2c9402aa77f3bc4b193abbb.

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Results and Discussion

Speech segmentation

To analyze speech segmentation performance, our mixed-effects logistic regression had selection of the target word (either correct or incorrect) as our outcome variable and chance level (logit of 0.5) and language (Balanced, Aligned, Conflict, respectively) as predictor variables. Our initial model had a maximal random structure with stimuli as random slopes and participants as random intercepts[3] (Barr et al., 2013), but this model did not converge. We then pruned it to include only random intercepts for stimuli and participants[4].

Participants from the Balanced language were much more likely to select the words over the part-words at test (*Odds Ratio* = 10.95, 95% CI [4.19, 28.57][5]; *M* = 0.85,

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[3] lme4 syntax: selection ~ chance level + language + (stimuli|participant)

[4] lme4 syntax: selection ~ chance level + language + (1|stimuli) + (1|participant).

[5] Regression tables are available at https://osf.io/rs2bm/?view_only=95970ffcb2c9402aa77f3bc4b193abbb

SD = 0.16; Figure 2). Participants from the Aligned language, in which both TP and phonotactic probability pointed to word boundaries, were even more likely to select words over part-words (change in *OR* = 1.61, 95% CI [0.41, 6.27]; *M* = 0.87, *SD* = 0.18). On the other hand, participants from the Conflict language, in which TP and phonotactic probabilities worked against each other, were equally likely to select words and part-words (change in *OR* = 0.13, 95% CI [0.04, 0.42]; *M* = 0.57, *SD* = 0.3). These results are in line with our previous findings that adults not only track both TP and PP at the same time, but that these statistics can be combined to improve (i.e., Aligned language) or impair (i.e., Conflict language) speech segmentation (Dal Ben et al., 2021).

In addition, segmentation performance and self-evaluation (Figure 2) were positively correlated for the Balanced (r_s = 0.45) and Aligned (r_s = 0.48) languages, but not for the Conflict language (r_s = 0.12). This might suggest that the combination of TP and PP statistics might increase or decrease the likelihood of adults treating newly segmented sounds as more or less word-like.

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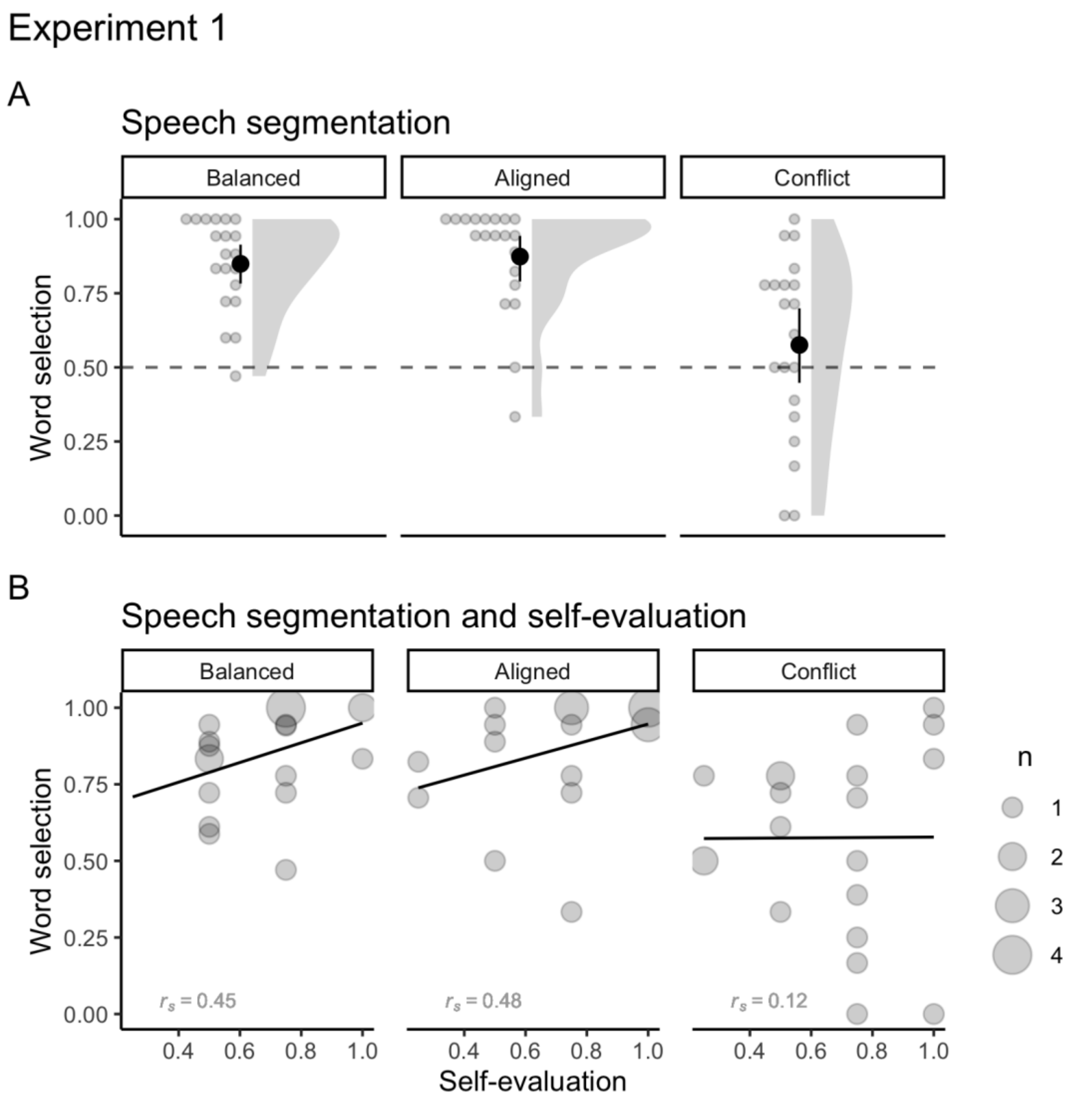

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Figure 2. Panel A: Mean number of correct word selections for Balanced (*M* = 0.84, *SD* = 0.15), Aligned (*M* = 0.87, *SD* = 0.18), and Conflict (*M* = 0.57, *SD* = 0.3) languages on segmentation test of Experiment 1. Solid points represent the overall mean, error bars represent 95% CIs (non-parametric bootstrap). Points represent the mean for each participant. Shaded areas depict the distribution of individual responses. The dashed line displays the chance level (0.5). Panel B: Correlations between segmentation and self-evaluation (upper panel; $r_{s\ Balanced} = 0.45$; $r_{s\ Aligned} = 0.48$; $r_{s\ Conflict} = 0.12$) for Balanced, Aligned, and Conflict languages on Experiment 1. The size of dots indicates the number of participants that overlap in given coordinates (from 1 to 4).

To explore whether our joint task impacts speech segmentation, we compared the present data with data from a previous investigation testing speech segmentation only (Dal Ben et al., 2021). Because we used the exact same languages as previous studies, we fit separate mixed-effects logistic regressions[6] for each language (Balanced, Aligned, Conflict), having the selection of target words (correct or incorrect) as our outcome variable, experiment (segmentation only or simultaneous task) as a predictor variable, and participants as random intercepts.

For the Balanced language, participants in the simultaneous task were approximately three times more likely to choose the target word compared to the separate task (change in *OR* = 3.21, 95% CI [1.50, 6.88]; Figure 3). The difference was even higher for the Aligned language, participants from the simultaneous task were almost five times more likely to make correct selections in comparison to the separate task (change in *OR* = 4.93, 95% CI [1.34, 18.16]). On the other hand, in the Conflict language, although participants in the simultaneous task still outperformed participants from the separate task, the improvement was much less pronounced (change in *OR* = 1.96, 95% CI [0.83, 4.64]).

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[6] lm4 syntax for each language: word selection ~ experiment + (1|participant)

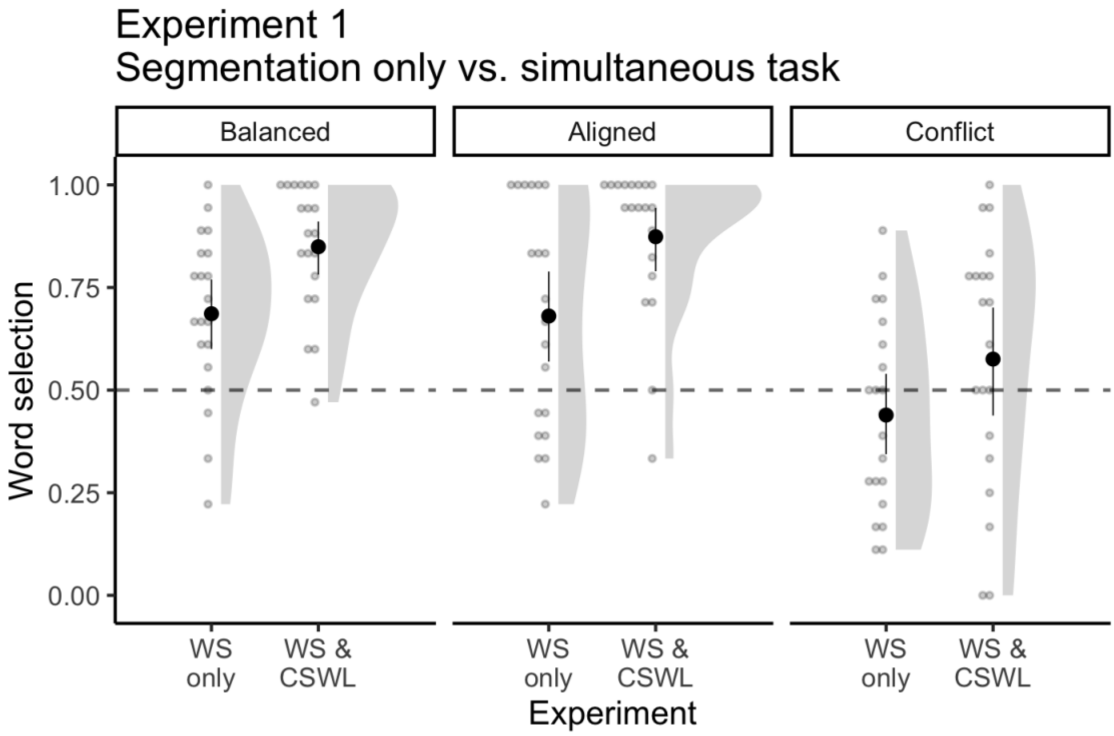

Figure 3. Mean number of correct word selections for Balanced (separate: *M* = 0.68, *SD* = 0.2; simultaneous: *M* = 0.84, *SD* = 0.15), Aligned (separate: *M* = 0.68, *SD* = 0.27; simultaneous: *M* = 0.87, *SD* = 0.18), and Conflict (separate: *M* = 0.43, *SD* = 0.23; simultaneous: *M* = 0.57, *SD* = 0.3) languages for an experiment testing speech segmentation only (WS only; Dal Ben et al., 2021) and on our current simultaneous task (WS & CSWL). Solid points represent the overall mean, error bars represent 95% CIs (non-parametric bootstrap). Points represent the mean for each participant. Shaded areas depict the distribution of individual responses. Dashed line displays the chance level (0.5).

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These results show that adults will use any statistic available–phonetic and audiovisual co-occurrences–to find words in continuous speech. Moreover, the improvement in segmentation in a more complex task indicates that adults benefit from tracking multiple statistical sources. This provides initial empirical support for the model proposed by Räsänen and Rasilo (2015) and is in line with recent research on language development in natural environments (Clerkin et al., 2017; Smith et al., 2018; Yu et al., 2021).

Cross-situational word learning

To analyze cross-situational word learning, our mixed-effects logistic regression[7] had selection of the target object (either correct or incorrect) as the outcome variable, chance level (logit of 0.25), language (Balanced, Aligned, Conflict, respectively), pair frequency (low or high), and their interaction as predictor variables, and stimuli and participants as random intercepts.

Across all languages and pair frequencies, participants were much more likely to select the correct object in comparison to the distractors (Figure 4; full regression table available at https://osf.io/rs2bm/?view_only=95970ffcb2c9402aa77f3bc4b193abbb). Mapping and self-evaluation (Figure 4) were positively correlated for all languages. They were strongly correlated for the Balanced language (r_s = 0.9), and moderately for the Aligned (r_s = 0.59) and the Conflict languages (r_s = 0.53). This suggests that participants from all languages were able to form clear word-object relationships. It was surprising to see that participants from the Conflict language, who performed at chance on the speech segmentation task, were able to form strong word-object relationships–a point to which we return later.

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[7] lm4 syntax: object selection ~ chance level + language * pair frequency + (1|stimuli) + (1|participant)

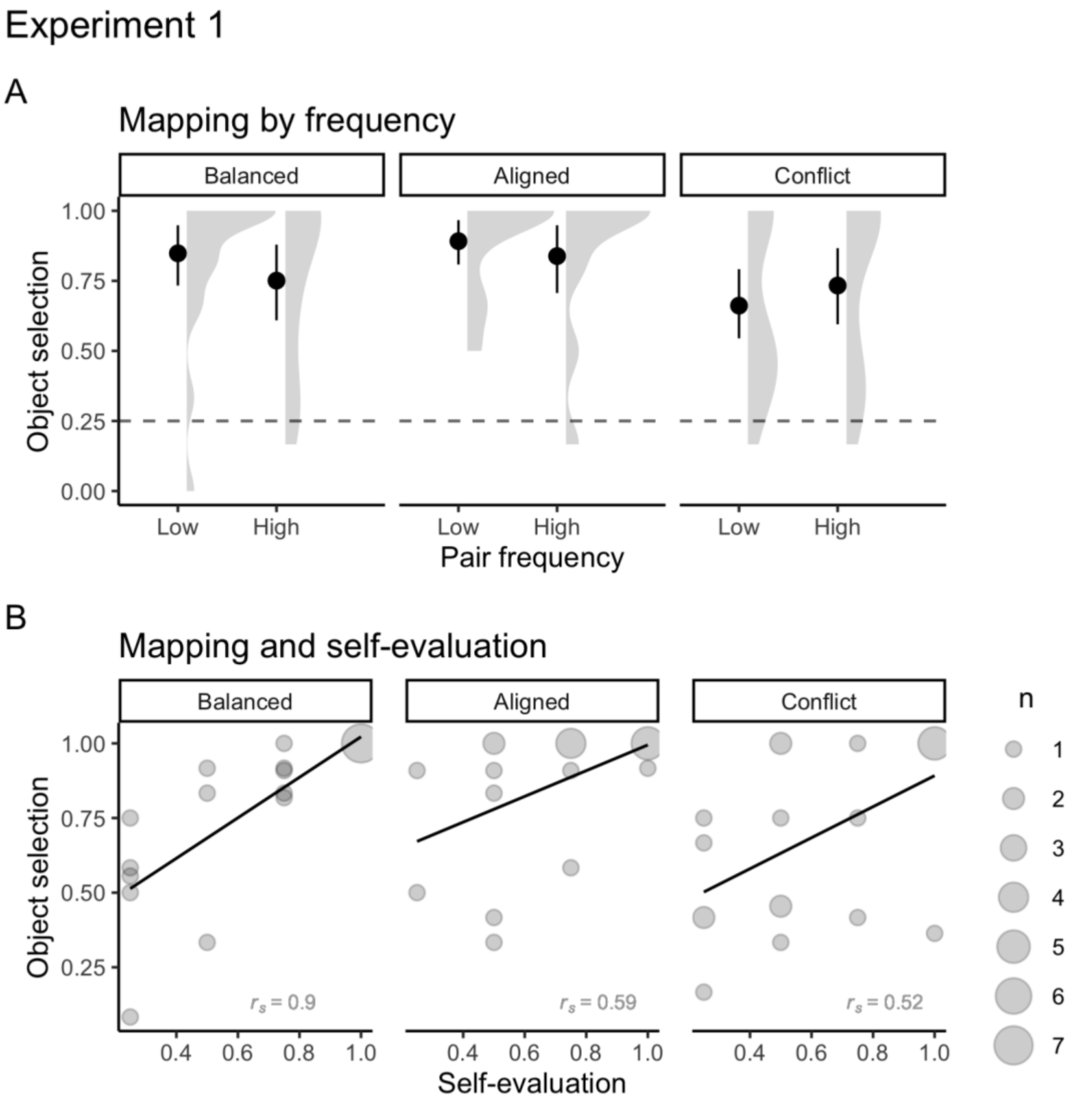

Figure 4. Panel A: Mean number of correct high and low frequency object selections for Balanced, Aligned, and Conflict languages on cross-situational word learning test of Experiment 1 (Balanced: M_{low} = 0.85, SD = 0.26, M_{high} = 0.75, SD = 0.3; Aligned: M_{low} = 0.89, SD = 0.18, M_{high} = 0.84, SD = 0.28; Conflict: M_{low} = 0.49, SD = 0.31, M_{high} = 0.56, SD = 0.32). Solid points represent the overall mean, error bars represent 95% CIs (non-parametric bootstrap). Shaded areas depict the distribution of individual responses. The dashed line displays the chance level (0.25). Panel B: Correlations between cross-situational word learning and self-evaluation for Balanced, Aligned, and Conflict languages ($r_{s\ Balanced}$ = 0.9; $r_{s\ Aligned}$ = 0.59; $r_{s\ Conflict}$ = 0.52) on Experiment 1. The size of dots indicates the number of participants that overlap in given coordinates (from 1 to 7).

To explore whether our simultaneous task impacts mapping performance, we compared the present data with data from a previous experiment that only tested cross-situational word learning but using the same stimuli and population (Dal Ben et al., 2022). We fitted one mixed-effect logistic model that had mapping (correct or incorrect) as the outcome variable, the interaction between experiment (separate or simultaneous task) and language (Balanced, Aligned, Conflict) as a predictor, and participants as random intercepts[8].

Overall, cross-situational word learning improved for all languages during the parallel task in comparison to the separate task (Figure 5). The improvement was greater for participants from the Aligned language (change in *OR* = 7.39, 95% CI [2.10, 25.98]), followed by participants from the Balanced language (change in *OR* = 3.34, 95% CI [1.37, 5.52]). Although less pronounced, there was also an improvement for the Conflict language (change in *OR* = 1.60, 95% CI [0.50, 5.05]), which indicates that participants can benefit from word-object co-occurrence even when TP and phonotactics point to different word boundaries.

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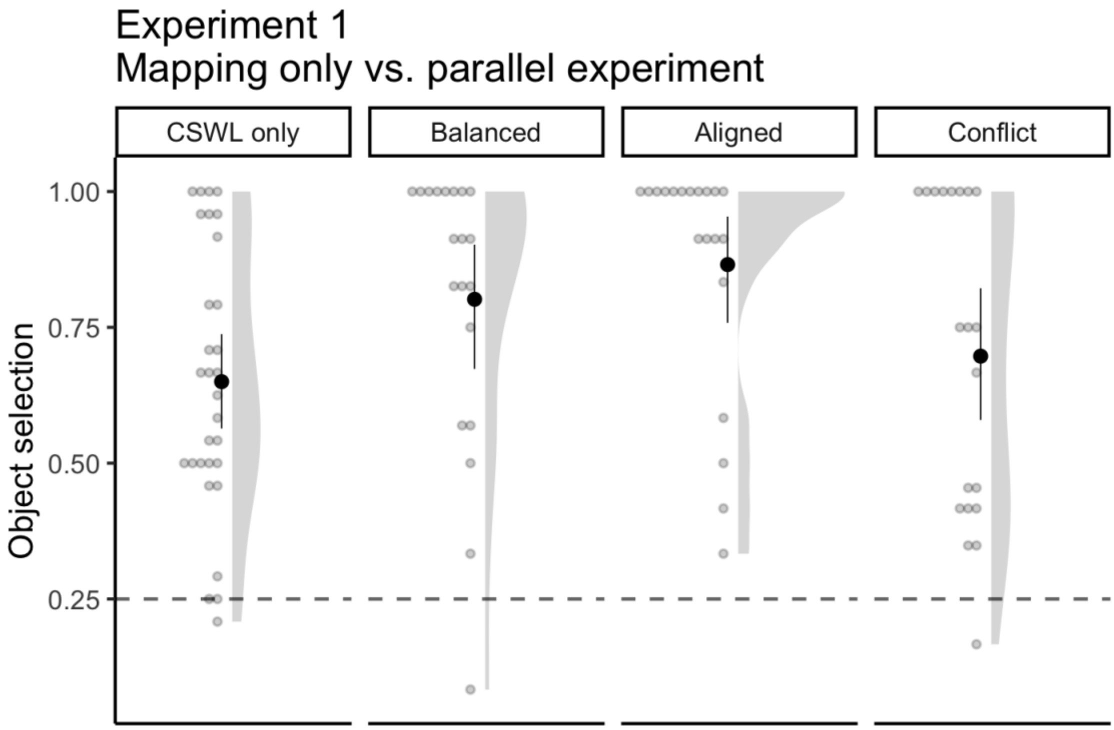

Figure 5. Mean number of correct object selections in an experiment testing cross-situational word learning only–CSWL only (*M* = 0.65, *SD* = 0.24; Dal Ben et al., 2022)–and in the Balanced (*M* = 0.79,

[8] lme4 syntax: object selection ~ experiment:language + (1|participant)

SD = 0.28), Aligned (*M* = 0.86, *SD* = 0.23), and Conflict (*M* = 0.69, *SD* = 0.3) languages from the present, simultaneous, experiment. Solid points represent the overall mean, error bars represent 95% CIs (non-parametric bootstrap). Points represent the mean for each participant. Shaded areas depict the distribution of individual responses. Dashed line displays the chance level (0.25).

Relationship between speech segmentation and word mapping

To explore potential relationships between speech segmentation and word mapping, we ran Spearmans' correlations between words' and objects' selections (average scores per participant) for each Language. We found moderate positive correlations between segmentation and mapping for all Languages ($r_{s\ Balanced}$ = 0.49; $r_{s\ Aligned}$ = 0.52; $r_{s\ Conflict}$ = 0.42; Figure 6, panel A). Overall, participants that were better at segmentation were also better at mapping. To further explore if that was true for participants from the Conflict Language, we performed a median split of segmentation performance (*Mdn* = 0.66, *IQR* = 0.4) and ran Spearman correlation tests for each group separately (Figure 6, panel B). Participants that successfully segmented the speech (above median) were also successful in mapping words to objects (r_s = 0.46). However, we found no relationship between segmentation and mapping for those who performed poorly on segmentation (below the median; r_s = 0.003).

Our design does not inform us about potential learning sequences. Intuitively, strong speech segmentation skills should lead to strong word mapping, which is confirmed to some extent by the positive correlation between word and object selections for participants above the median in the Conflict language, but not for those below the median. Interestingly, simulations by Räsänen and Rasilo (2015) favor a simultaneous performance in which speech segmentation and mapping retrofeed each other, driving performance on both tasks. In this regard, the absence of a relationship between segmentation and mapping for participants below the median in the Conflict Language indicates that these performances could be independent from one another.

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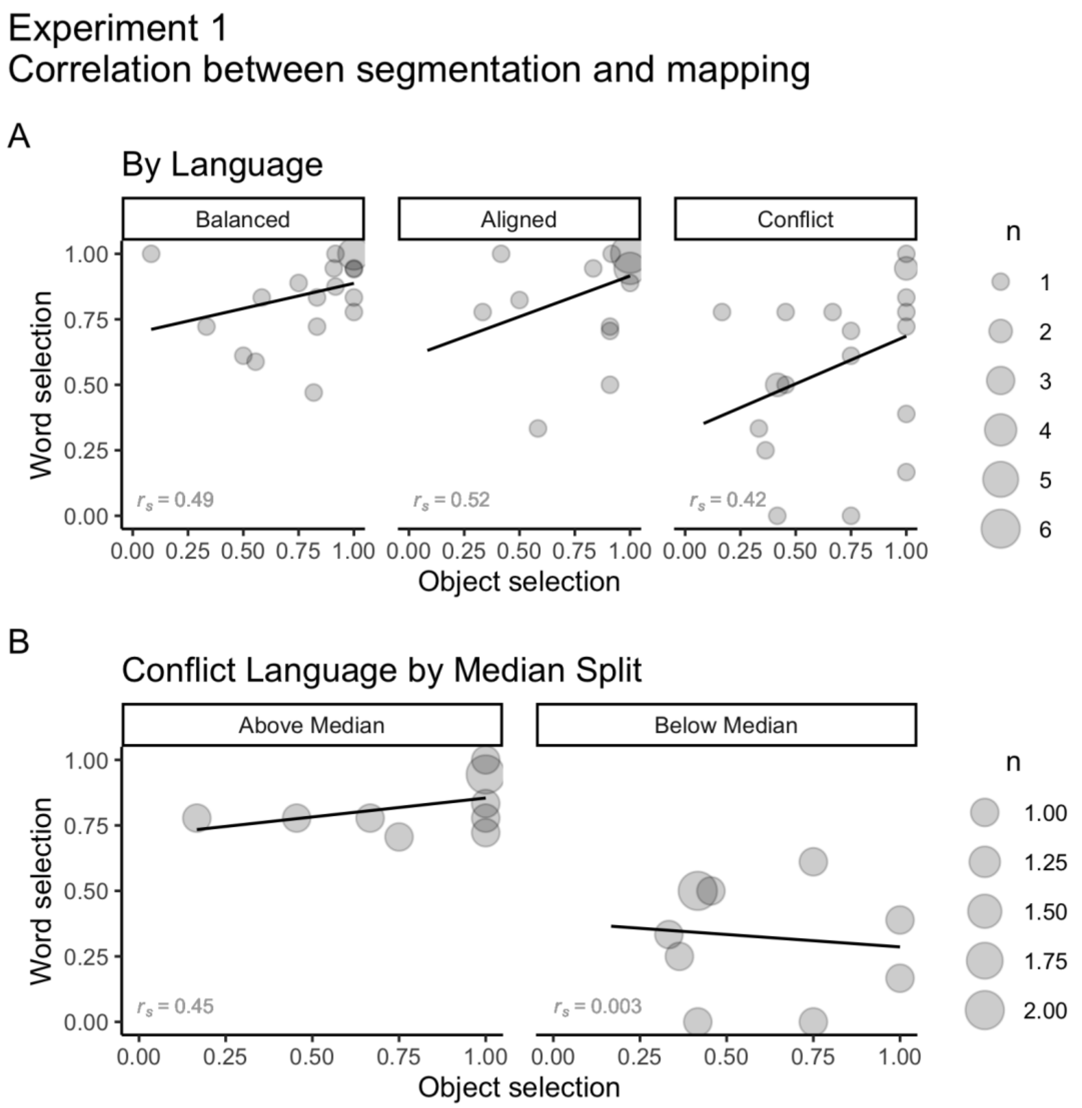

Figure 6. Panel A: Correlations between speech segmentation and mapping for Balanced, Aligned, and Conflict Languages on Experiment 1 ($r_{s\,Balanced} = 0.49$; $r_{s\,Aligned} = 0.52$; $r_{s\,Conflict} = 0.42$). The size of dots indicates the number of participants that overlap in each coordinate (from 1 to 6). Panel B: Correlations between speech segmentation and mapping in the Conflict Language for participants with speech segmentation above the median (*Mdn* = 0.66, *IQR* = 0.4; $r_s = 0.45$) and below the median ($r_s = 0.003$). The size of dots indicates the number of participants that overlap in each coordinate (from 1 to 2).

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Overall, results from the present experiment suggest that not only can adults simultaneously track conditional probabilities between audio and visual stimuli to segment words from continuous speech streams and map them to referents under ambiguous learning contexts, but that segmentation and mapping improve with complexity (Figures 3, 5). Such results provide preliminary empirical evidence to the model of simultaneous segmentation and ambiguous mapping proposed by Räsänen and Rasilo (2015).

Our results also indicate that phonotactic probabilities, or how familiar syllables' positional probabilities are in the native language of the participants, also impact such joint performance. When transitional and phonotactic probabilities worked together to signal word boundaries, segmentation and mapping improved (Aligned language) in contrast to when the phonotactic probabilities were balanced among test items (Balanced language). However, the impact of phonotactics was most pronounced when it was in conflict with TP information. In the Conflict language, overall, participants failed to show a preference for words when compared to part-words at test (Figure 2). Nonetheless, they were able to map words and objects (Figure 4). How could this happen?

If we assume that segmentation is a necessary pre-step to cross-situational mapping, then this result is hard to explain. However, if adults use whatever informative statistics they have at hand to solve linguistic ambiguity, they would take advantage of both transitional and phonotactic statistics and word-object co-occurrences in the Aligned and Balanced languages. On the other hand, in the Conflict language, statistics were not consistent enough to promote segmentation, but co-occurrences between syllables and objects were consistent enough to promote mapping—even without clear and explicit word representations.

Moreover, our two-alternative forced-choice test might not have been sensitive enough to capture the weaker and implicit word representations that might have arisen in the Conflict language, providing us a partial picture of participants' speech segmentation. Our two-alternative-forced-choice trials contrasted words with stronger TPs and weaker phonotactic probability, or part-words with weaker TPs but stronger

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phonotactic probability. The contrast between recently acquired TP knowledge, and language specific phonotactic knowledge learned across the lifespan, may have impaired word selection (Finn & Hudson Kam, 2008). With this in mind, we replicate the current study, but using an arguably more sensitive speech segmentation measurement.

Experiment 2

In an attempt to capture the potentially nuanced word form knowledge implicitly arising from experience with the Conflict language, in the current experiment we use a more sensitive word segmentation test: go/no-go (François et al., 2017). In this test, each item is presented and evaluated separately, one at a time. By avoiding the contrast between stimuli (i.e., word, part-word, non-word) with different statistics (TP and phonotactics) at test and by adding a new stimuli type (i.e., non-words), we aim for a more fine-grained understanding of word representations in the Conflict language.

Method

This experiment was a replication of Experiment 1, but it was fully online due to the COVID-19 pandemic. Differences in methodology are described below.

Participants

Forty-five adults, all native speakers of Brazilian-Portuguese, with no reported visual or auditory impairment that could interfere with the task, participated. However, 10 participants were excluded from the final analyses because they failed or missed attention check questions, reported using their mobile phones or taking notes during the experiment (see Data Analysis for further details). The final sample consisted of 35 adults (M_{age} = 23.51, ± 4.01 *SD*, 22 female). As in Experiment 1, participants were recruited at the official Facebook group of the [ANONYMIZED] and received no compensation for their participation. The study was conducted according to the

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Declaration of Helsinki and the Ethics Committee of the host university approved the research (#3.085.914).

Stimuli and Design

We used the Conflict language from Experiment 1, with the same word-object pairs. As a brief reminder, in this Language, words had high TPs (TP = 1; Table 1) and lower phonotactic probabilities (M_{words} = 0.0072), while part-words had lower TPs (TP = 0.5) and higher phonotactic probabilities ($M_{part\text{-}words}$ = 0.0085). In addition, we created three additional non-words with balanced phonotactic by recombining the initial syllables of words (i.e., /visu/, /tami/, /rako/; PPs = 0.0080, 0.0074, 0.0069, respectively). Because their syllables never occurred together in the Language, their TP was zero.

A similar design from Experiment 1 was used here, with four main differences. First, given the online nature of the study, before beginning the experimental task, participants were instructed to move to a quiet room, to turn off any electronic devices (e.g., cellphone, TV), to wear earphones, and not to take notes during the experiment. Second, the segmentation test followed a go/no-go structure: test words (i.e., /nipe/, /tadi/, /mide/), part-words (i.e., /sute/, /viko/, /bara/), and non-words (i.e., /visu/, /tami/, /rako/) were presented one at a time and participants were instructed to indicate whether they were or were not words from the language they had just heard (by pressing to “s” or “n”, corresponding to “sim” [yes] or “não” [no] in Portuguese). Each stimuli was tested 6 times (total of 54 trials). Third, attention checks were conducted during the familiarization and segmentation test. At each familiarization block, participants were prompted to answer five simple questions (i.e., “Are you alive?”, “Are you sleeping?”, “Are you breathing?”, “Are you dead?”, “Are you awake?”). Between segmentation test trials, attention checks displayed either a Portuguese word or a made-up word (e.g.,

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"mesa" [table], "drevo") printed on the screen and participants were prompted to indicate if the word existed in Portuguese or not. During both familiarization and test, participants indicated their answers for attention checks by pressing the "s" or "n" keys on the keyboard. Fourth, at the end of the experiment, we checked for compliance to instructions by asking participants whether they had used the cellphone or if they had taken notes during the experiment.

Procedure

The experiment was entirely online, hosted on Pavlovia and programmed using Psychopy3 (Bridges et al., 2020). After agreeing to participate, participants were instructed to avoid distractions (see previous section), answered a questionnaire about their educational background and language abilities, and then started the experimental task. As in Experiment 1, they were exposed to three phases: familiarization, segmentation test, and mapping test. In addition, attention checks (described before) were presented between familiarization blocks and between trials during the segmentation test.

Data Analysis

We followed similar analytical steps from Experiment 1. We first excluded participants who reported using their mobile phones during the experiment (n = 3) and those (n = 2) who failed two or more attention checks (out of five questions) during familiarization. Another five participants were excluded because their reaction times to attention checks in the familiarization or segmentation tests were greater than 3 SDs from the mean. For the remaining participants (n = 35), we excluded trials with reaction times greater than 3 SDs away from the mean (segmentation: 32 trials overall, 1% of the data; mapping: 7 trials overall, 1% of the data). The final data was entered in mixed-

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effect logistic regressions. The outcome, predictors, and random effects for each model is described in the next section.

Results and Discussion

Speech segmentation

To analyze speech segmentation, we fitted a mixed-effects logistic regression with words', part-words', and non-words' evaluations as the outcome variable. Selection of words and rejections of part-words and non-words were coded as correct responses. Predictors were the chance level (logit of 0.5) and stimuli type (words, part-words, non-words), stimuli and participants were random intercepts[9].

We replicated the results from Experiment 1 – Conflict language. Overall, participants' performance was at chance level (M = 0.51, SD = 0.15; Figure 7, panel A). The analyses by stimuli type (Figure 7, panel C) reveal a slight tendency for evaluating words as such (OR = 1.21, 95% CI [0.61, 2.4]), a stronger tendency for correctly rejecting non-words (change in OR = 1.68, 95% CI [0.67, 4.2]), and a much less accurate judgment when rejecting part-words (change in OR = 0.41, 95% CI [0.16, 1.03]). As in Experiment 1, there was no correlation between speech segmentation and self-evaluation ($r_{s\ Conflict}$ = 0.08).

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[9] lme4 syntax: selection ~ chance level + stimuli type + (1|stimuli) + (1|participant).

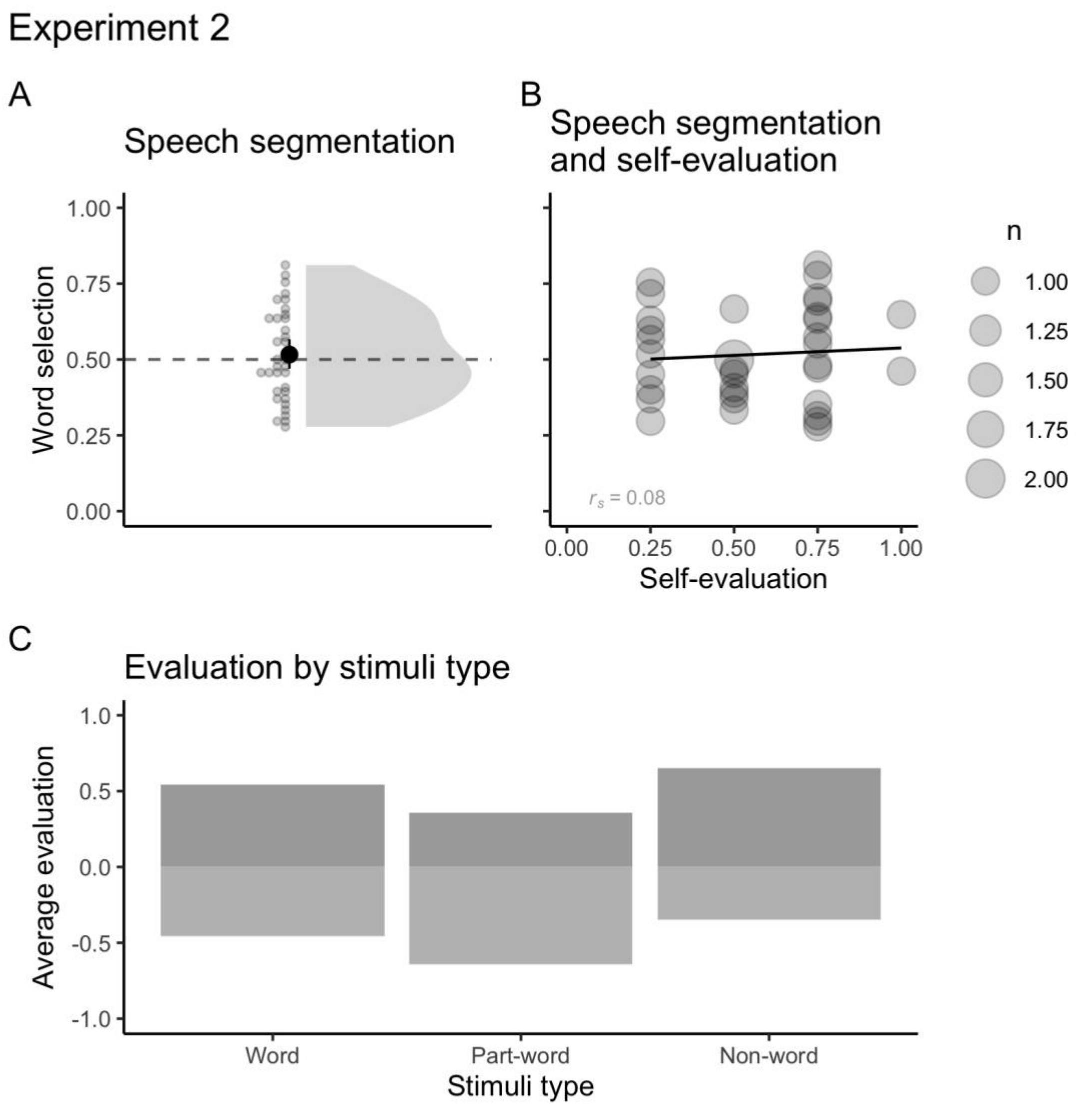

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Figure 7. Panel A: Mean number of correct word selections and part-word and non-word rejections on Experiment 2 (M = 0.51, SD = 0.15). The solid point represents the overall mean, error bars represent 95% CIs (non-parametric bootstrap). Points represent the mean for each participant. The shaded area depicts the distribution of individual responses. The dashed line displays the chance level (0.5). Panel B: Correlations between segmentation and self-evaluation ($r_{s\ Conflict}$ = 0.08) on Experiment 2. The size of dots indicates the number of participants that overlap in given coordinates (from 1 to 2). Panel C: Evaluation by stimuli type (word, part-word, non-word). Positive scores represent correct selection of words (M = 0.54, SD = 0.28) and rejection of part-words (M = 0.35, SD = 0.25) and non-words (M = 0.65, SD = 0.27). Negative scores represent incorrect rejections of words and selection of part-words and non-words.

These results indicate that participants might have tracked both transitional and phonotactic statistics from familiarization, but used them differently when evaluating stimuli during test. For instance, they might have relied on TP information when evaluating words (higher TP and lower phonotactics) and phonotactic information when evaluating part-words (lower TP and higher phonotactics). Finally, the lack of familiarity with non-words (no TP information), and the balanced phonotactic statistics, might have generated correct non-word rejections. Overall, our nuanced results could indicate that the go/no-go procedure is not sensitive enough to capture implicit word representation arising from speech segmentation of a language with conflicting statistics–a point we return to in the General Discussion.

Cross-situational word learning

To model mapping performance, our mixed-effect logistic regression had object selection (correct or incorrect) as the outcome variable, chance level (logit of 0.25) and target stimuli frequency (150 or 300 repetitions) as predictors, and stimuli and participants as random intercepts[10]. As in Experiment 1, participants correctly mapped both high and low frequency words above chance level (M_{high} = 0.56, SD_{high} = 0.31; M_{low} = 0.49, SD_{low} = 0.31; Figure 8), with small differences in the likelihood of correctly selecting high or low frequency word-object pairs (OR_{high} = 1.51, 95% CI [0.75, 3.02]; change in OR_{low} = 0.68, 95% CI [0.35, 1.36]). Again, we found a moderate positive correlation between mapping and self-evaluation (r_s = 0.67; Figure 8).

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[10] lme4 syntax: selection ~ chance level + target frequency + (1|stimuli) + (1|participant).

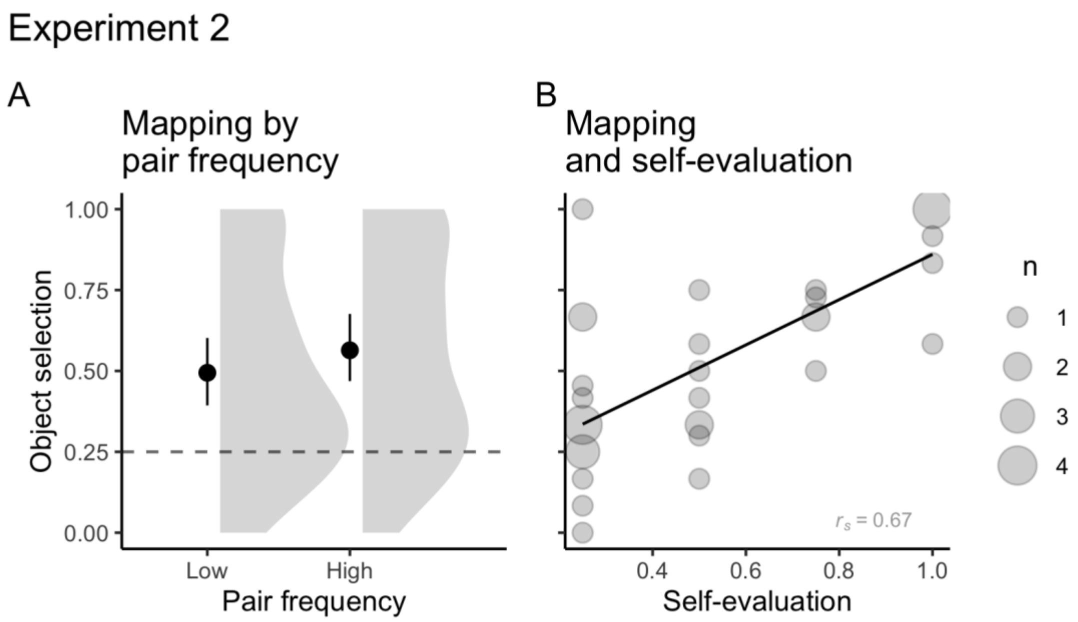

Figure 8. Panel A: Mean number of correct object selections for high (*M* = 0.56, *SD* = 0.31) and low (*M* = 0.49, *SD* = 0.31) frequency pairs on Experiment 2. The solid point represents the overall mean, error bars represent 95% CIs (non-parametric bootstrap). The shaded area depicts the distribution of individual responses. The dashed line displays the chance level (0.25). Panel B: Correlations between mapping and self-evaluation ($r_{s\ Conflict}$ = 0.67) on Experiment 2. The size of dots indicates the number of participants that overlap in given coordinates (from 1 to 4).

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Relationship between speech segmentation and word mapping

As in Experiment 1, we ran Spearmans' correlation tests between words' and objects' selections (average scores per participant) to explore potential relationships between speech segmentation and word mapping. We found a weak positive correlation between segmentation and mapping (r_s = 0.32; Figure 9). Again, overall, participants that were better at segmentation were also better at mapping. Further exploration by speech segmentation median split (*Mdn* = 0.5, *IQR* = 0.24) revealed little difference between participants above the median (r_s = 0.05) and below the median (r_s = 0.11), with no correlation between segmentation and mapping for both groups.

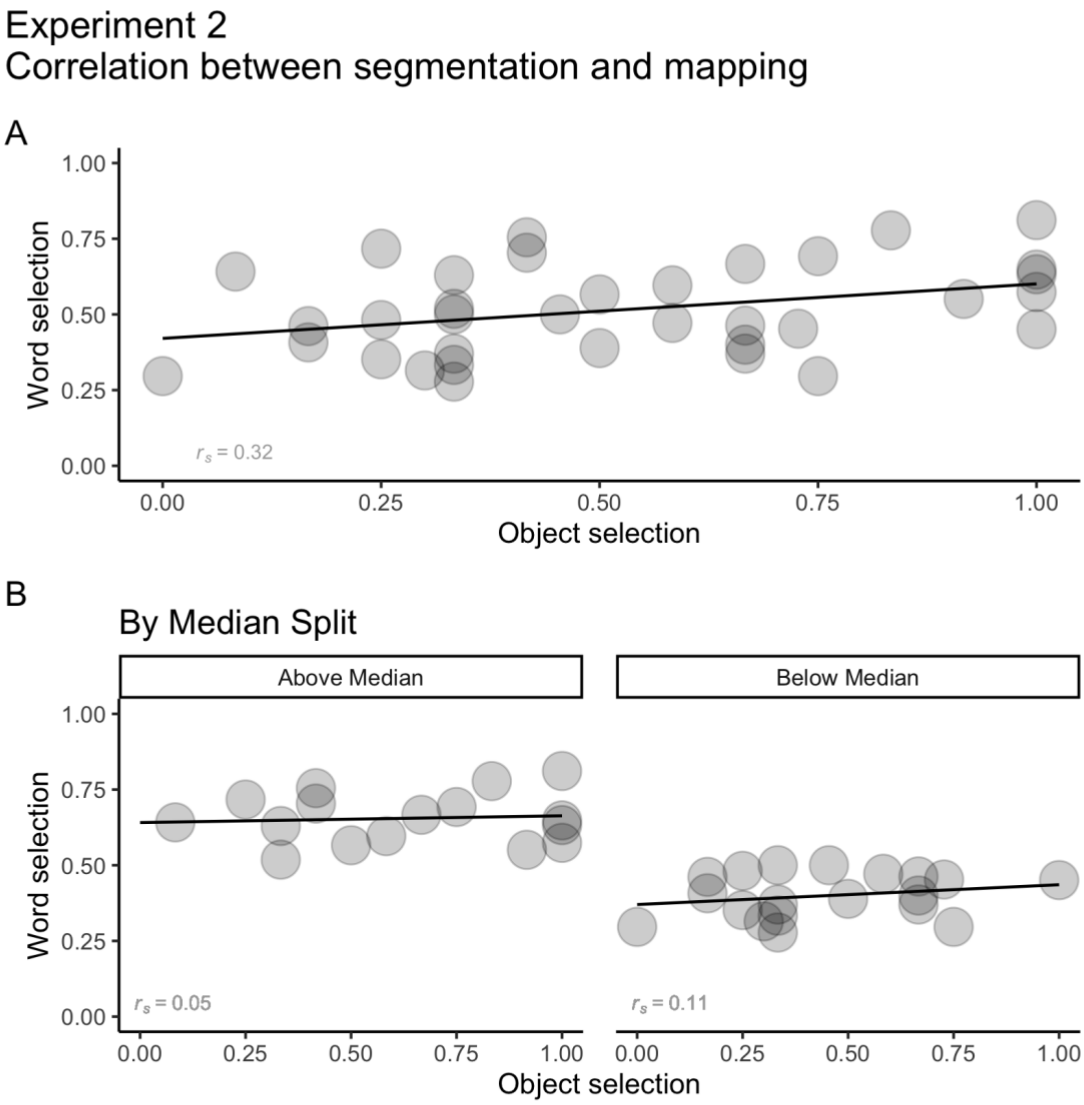

Figure 9. Panel A: Correlation between segmentation and mapping (r_s = 0.32) on Experiment 2. Panel B: Correlations between speech segmentation and mapping for participants with speech segmentation above the median (*Mdn* = 0.5, *IQR* = 0.24; r_s = 0.05) and below the median (r_s = 0.11).

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The current experiment was designed to further evaluate the effects of the conflict between transitional and phonotactic statistics on simultaneous speech segmentation and cross-situational word learning. Overall, we replicated Experiment 1: speech segmentation, as measured by a go/no-go test, was at chance level, but word-object mapping performance was above chance. Nonetheless, our more sensitive word segmentation test provided some nuanced information about stimulus representations.

We found that participants were likely to correctly evaluate non-words as such. This indicates that how participants represented words and part-words was most likely the result of the interplay between phonotactic and transitional probabilities. For instance, stronger phonotactics combined with a probabilistic transitional probability (TP = 0.5) lead participants to incorrectly evaluating part-words as words. On the other hand, the weaker phonotactics combined with deterministic transitional information (TP = 1) prompt only a slight tendency to correctly evaluate words as such.

As in Experiment 1, speech segmentation performance and self-evaluation indicates that the conflict between transitional and phonotactic probabilities impaired the formation of a more explicit word representation. Again, however, despite the absence of clear word representations, participants were able to map words to objects. Word-object co-occurrences might have provided sufficient information to promote mapping and some level of segmentation, despite conflicting phonetic information (Räsänen & Rasilo, 2015). Next, we address some of the limitations of our exploratory study and discuss how our preliminary findings broaden our understanding of statistical learning from multiple cues and prompt further research on the subject.

General Discussion

In the present study, we explored whether adults could segment speech streams into words and map them to objects simultaneously by tracking conditional probabilities across ambiguous presentations. In addition, we also investigated the effects of word-level phonotactics in segmentation and mapping. Phonotactics were either balanced, aligned, or in conflict with transitional probabilities. We found that participants were successful at both the segmentation and mapping tasks when transitional and phonotactic probabilities were either aligned or balanced across words. In contrast,

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when transitional and phonotactic probabilities were in conflict, we did not find evidence for speech segmentation, but we still found evidence for mapping.

Our results offer preliminary support for the idea that complexity supports speech segmentation and word learning in ambiguous situations (Räsänen & Rasilo, 2015). Not only were participants able to segment and map words simultaneously by tracking conditional probabilities, but their overall performance was stronger in this simultaneous task in comparison to separate tasks of segmentation and cross-situational word learning. This adds to the evidence showing that language learners benefit from combining several sources of linguistic information when learning a new language (Choi et al., 2018; Johnson, 2016; Saffran, 2020; Smith et al., 2018). The positive correlation between segmentation and mapping, found in all languages of both experiments, further suggests that a common learning mechanism might drive performance on both tasks. These findings are consistent with a domain-general statistical learning framework that spans across perceptual domains–in our case, auditory and visual (Frost et al., 2015).

Interestingly, the conflict between phonotactics and transitional information might have impaired the formation of clear and explicit word representations, but not the formation of strong word-object relationships. Whereas this could point to independent processing of phonetic and audiovisual statistics, it could also be that participants did form clear, but implicit, word representations that our explicit measurements (either a two-alternative forced-choice or go/no-go) were not able to capture. For instance, despite the conflict between transitional and phonotactic statistics, participants were still able to consistently reject non-words during Experiment 2, showing that stimuli with different degrees of statistical information were treated differently. A more direct way to assess implicit word representations may be to use

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EEG measures during the passive familiarization phase. Robust event related potentials have been reported for violations of words' transitional and phonotactic probabilities (e.g., Elmer et al., 2021; François et al., 2017). In an ongoing EEG study, we are measuring whether participants will show similar ERPs to violations of transitional and phonotactic information presented in the Balanced and in the Conflict languages.

Another invaluable source of information on the learning mechanisms involved in the simultaneous speech segmentation and mapping are the cognitive processes underlying such performances. For instance, auditory and visual memory have been shown to predict cross-situational word learning (Vlach & DeBrock, 2017; Vlach & Johnson, 2013). Differences in attention have also been found to impact statistical learning (Smith & Yu, 2013; Yurovsky et al., 2013). Future research could measure these and other cognitive processes to better understand their role in complex statistical language learning.

Our study was exploratory in nature. Building on our promising initial findings, future inferential replications should put our findings to the test. They could also address some of the shortcomings of the present investigation by having participants from heterogeneous populations. For instance, we tested fairly homogenous samples of young college students from a single language background. The trends we found may not generalize to other populations (Simons et al., 2017). Also, it could be that the statistical learning mechanisms involved in this simultaneous task may have different roles across development (Choi et al., 2018; Danielson et al. 2016; Smith et al., 2018). Future research could investigate simultaneous statistical language learning across development to bridge the gaps between young adults, infants, and older adults. Finally, although dynamic and fairly complex, our task comprises only a small sampling of the challenges (i.e., segmentation and mapping) and statistics (i.e., conditional probabilities)

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available for language learners in natural environments. Future studies could improve ecological validity by, for instance, using a natural language with statistical, prosodic, and semantic information (Hay et al., 2011; Karaman, 2018), or diving into natural environments (Bogaerts et al., 2022; Yu et al., 2021).

Learning languages is difficult. To overcome many linguistic challenges, learners can rely on several cues. Here we provide preliminary evidence that adults can track conditional probabilities to simultaneously find words in continuous speech and map them to objects across ambiguous situations. We also show that the level of pre-experimental familiarity with words can impact their representation. By doing so, we contribute to a more nuanced understanding of how statistical cues interact to promote language learning.

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