Statistical learning or phonological universals? Ambient language statistics guide consonant acquisition in four languages

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Abstract

What predicts individual differences in children's acquisition of consonant production across languages? Considerations of children's development of early speech production have traditionally emphasized inherent physiological constraints of the vocal apparatus that speakers generally have in common (i.e., articulatory complexity). In contrast, we propose a statistical learning account of phonological development, in which phonological regularities of the ambient language guide children's learning of those regularities in production. Across four languages (English, Spanish, Japanese, and Korean), we utilized recent meta-analytic dataset of age of consonant acquisition spanning 28 studies. High-density measures of children's ambient language environment from over 8,000 transcripts of speech directed to over 1,000 children were used to assess how well the frequency of consonants in child-directed speech predict the age of consonant acquisition. Our results suggest that both frequency and articulatory complexity are related to age of acquisition, with similar results found for English, Spanish, Japanese, and Korean. Consonants heard frequently by children tended to be incorporated into their production repertoires earlier and consonants heard less frequently are incorporated into production repertoires later in development. We discuss future directions that incorporate a statistical learning pathway towards learning to produce the sound patterns of the ambient language.

Keywords: speech production; language input; language statistics; child-directed speech; phoneme acquisition; statistical learning

Introduction

How do children learn to produce the consonant sounds of their ambient language? Traditional approaches have focused on the difficulty with which consonants are produced by speakers (Jakobson, 1941). This difficulty has been conceptualized as the articulatory complexity involved with producing a given consonant (Kent, 1992). A recent meta-analysis of children's consonant acquisition trajectories across 27 languages suggests that while some stability in consonant acquisition over development exists, there is also wide variation in consonant acquisition trajectories across and within languages, suggesting that consonant acquisition is not exclusively about articulatory complexity (McLeod & Crowe, 2018). For example, the consonant /f/ (as in *fork*) is relatively stable across and within languages (i.e., is characterized by low variance in its age of acquisition across languages), but the learning of /v/ (as in *vase*) appears to be guided more so by the extent to which children perceive its use in the ambient language (Crowe & McLeod, 2020; McLeod & Crowe, 2018).

Another source of variation in children's consonant acquisition may derive from the distribution of different consonants in the ambient language. Statistical learning—sensitivity to distributional patterns in the speech environment—has been a productive alternative research program to universalist claims of language acquisition (Frost, Armstrong, & Christiansen, 2019). Several lines of evidence suggest that infant vocal learning, including learning to produce consonant sounds, requires perceptual mechanisms to incorporate patterns of the ambient language into more mature vocalizations (Boysson-Bardies et al., 1991; Edwards et al., 2015; Edwards & Beckman, 2008; Goldstein & Schwade, 2008; Ingram, 1988). For example, compared to German-learning infants, Nso-learning infants produce significantly more click-like consonant sounds, a consonant pattern found mainly in the learning environment of Nso-learning infants (Wermke et al., 2013).

There are at least three reasons underlying the limited progress on fully understanding ambient language effects on consonant production learning in children. First, substantial quantifiable data on children's language environment has only recently become widely available to researchers (MacWhinney, 2000; Sanchez et al., 2019). Past consonant acquisition research was not able gain insights into the perceptual regularities present in child-directed speech, the sounds that children are most likely to encounter in their everyday learning environments. Additionally, access to high-density cross-linguistic data on children's consonant acquisition trajectories has only recently become possible (McLeod & Crowe, 2018).

Second, previous models of articulatory complexity (AC) are themselves based on age of acquisition data (Kent, 1992). For example, Kent (1992) based his analysis of articulatory complexity on previous documentation of age of acquisition of consonants found by Sander (1972) and Dinnsen et al. (1990). AC classifications were inferred from the observed order in which English-learning infants and children learned to produce consonants. Historically, the directionality of this inference has been overlooked (i.e., age of consonant acquisition → articulatory complexity), and findings have been interpreted with the assumption that articulatory complexity explains acquisition trajectories (e.g., late

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acquired consonants must be more complex). These misleading interpretations underestimate the role of the ambient language and children's statistical learning capacities in consonant acquisition. Ambient language environments afford several regularities including variation in consonant functional load (i.e., the extent to which a consonant contrast distinguishes between words), and perceptual salience (Stokes & Surendran, 2005).

Third, theoretical advances in the statistical learning approach to language acquisition have rarely been applied to the understanding of how children learn to produce the sounds of their ambient language. There is variation in age of consonant acquisition in children's production across languages (McLeod & Crowe, 2018). To better understand where this variation comes from, we predicted differences in age of consonant acquisition, across languages, based on ambient consonant frequency regularities present in the learning environment.

In the present study, we inspected individual consonants for their variation in age of acquisition across four languages: English, Spanish, Japanese, and Korean . We investigated the word-initial frequencies of mothers' and fathers' speech found in the CHILDES database for each language (MacWhinney, 2000). Word-initial frequencies were used because children are generally known to allocate attention to the onsets of words (Stokes & Surendran, 2005; Vihman et al., 2004). Under the *statistical learning hypothesis*, the consonants children encounter frequently in perception should predict age of consonant acquisition across languages. Here, we use a semi-naturalistic measure of the ambient speech sounds children encounter during language acquisition. Under the *articulatory complexity hypothesis*, articulatory complexity categories based on Kent (1992) should predict age of consonant acquisition across languages.

Methods

Corpora

Semi-naturalistic child-directed speech corpora were used to calculate the word-initial consonant frequencies for English, Spanish, Japanese, and Korean available on the CHILDES database (MacWhinney, 2000). These languages are the central focus of this work because their age of consonant acquisition data is drawn from 4 or more studies in the meta-analysis of McLeod and Crowe (2018). Child-directed speech to children aged 72 months maximum from the target child's mother or father was included. Only speech categorized as monolingual in CHILDES was used. We used the *childesr* package in R to extract CHILDES transcripts (Sanchez et al., 2019).

To obtain consonant frequency counts, we used eSpeak NG (Dunn, 2022) for grapheme-to-phoneme conversion of English, Spanish, Japanese, and Korean CHILDES transcripts, resulting in IPA transcriptions of all lexical types in each corpus (Dunn, 2022). For English, we used the US English setting, and for Spanish, we used the Latin American Spanish setting as a majority and all of the studies respectively reported them as the dialect of their subjects. From these, we took only the consonant-initial words and extracted the onset of the word, including consonant clusters. The frequency of each consonant in each corpus is computed by summing the token count of each lexical type where the consonant appears in the onset either as a singleton or within a cluster. To compare the various corpora obtained from CHILDES, we computed the frequency per million tokens for each consonant within each cluster. Moreover, due to the known skewed of frequency measures, we transformed this measure by taking its natural logarithm. Statistical models for each language use the mean of this log-transformed frequency per million averaging across all corpora for that language (F).

Because our hypothesis concerns naturalistic speech input, we excluded all corpora that document scripted and lab-based interactions[1]. Moreover, we also excluded bilingual corpora (Spanish: "SerraSole"). Finally, we excluded corpora with fewer than 1,000 tokens (English: "Fletcher" [86 tokens] "McMillan" [450 tokens], Spanish: "Marrero" [312 tokens], Japanese: "Ota" [13 tokens]). The data that met our inclusion criteria amounted to 60 corpora containing 8,517 unique transcripts of child-directed speech to 1,289 children with registered identification numbers. The final count for each language is 41 corpora with 5,775 transcripts and 914 children for English; 8 corpora with 669 transcripts and 170 children for Spanish; 7 corpora with 714 transcripts and 118 children for Japanese; and 3 corpora with 193 transcripts and 32 children for Korean. From eSpeak-NG's transcription resulted a total of 122,417 IPA word types (English: 33,548; Spanish: 11,788; Japanese: 34,781; Korean: 42,300) and 12,644,104 IPA word tokens (English: 10,560,571; Spanish: 479,928; Japanese: 1,256,722; Korean: 346,883).

Consonant acquisition data

To determine the age of consonant acquisition (AoCA) per consonant across languages, we used the meta-analytically determined mean ages (in months) of acquisition reported in McLeod and Crowe (2018). Statistical models use the within-study min-max normalized age (A). AoCA was the minimum age at which either 75% or 90% (depending on the study) of the participants in a given study produced a consonant correctly. In the case a given study had data for both criteria, we kept the one with the highest criterion. English AoCA data was derived from 15 different studies, Japanese from 5 studies, Korean from 4 studies, and Spanish from 4 studies.

From all the consonants included in McLeod and Crowe (2018), we analyzed only those that have at least 1 appearance in the onset in all of the CHILDES corpora for

[1] Corpora omitted for each language because of scripted interactions. English: Bernstein, Bohannon, Fletcher, Gelman, HSLDD, New England. Spanish: DiezItza. Japanese: Miyata.

their respective language. For Spanish, we omitted some of the consonants reported in only 1 study that tested different individual realizations of some of the canonical consonants (/ŋ/, /β/, /ð/, /ʒ/, /ʤ/, /ŋ/, /ð/, /ʒ/, /ʤ/). The result of this filtering is 21 consonants for English, 17 for Spanish, 20 for Japanese, and 18 for Korean.

Articulatory complexity

The AC of each consonant in our study was taken from Kent (1992), who categorized the consonant inventory of English into 4 categories of increasing difficulty (*C*). Extensions beyond English, not included in Kent (1992), were taken from various other sources that have classified consonants using the same categories: Stokes and Surendran (2005), Cychosz (2017) and Paul (2010) for Spanish and Japanese consonants, and Kang (2021) for Korean consonants. Conflicts between these sources were resolved by authors SM and KC. Table 1 shows the categorization of the complete consonant inventory of the study.

Table 1. Articulatory complexity categories (*C*) of the complete consonant inventory of the study.

C	Consonants
1	p, p*, m, n, h, w
2	b, d, k, g, f, j, ɸ, k*, kʰ, pʰ, t, t*, tʰ
3	l, ɹ, r, ɾ
4	ʤ, ʧ, s, v, ʃ, ð, θ, x, ç, cɕ, ɕ, ɟʑ, ts, z, ɕʰ, s*

Analytic approach

We employed linear models implemented in *R* (R Core Team, 2022) to predict age of consonant acquisition from ambient consonant frequency and articulatory complexity. The dependent variable for the models was the age of acquisition reported for each consonant in each of the studies for a language. The independent variables are the natural logarithm of the frequency per million tokens averaged across corpora for each consonant (*F*), and the articulatory complexity ranks described above (*AC)*.

Even though the dependent variable is a proportion bound by 0 and 1, it does not follow a binomial distribution. Thus, we followed the approach recommended in Warton and Hui (2011), transformed the normalized age using a logit function, and modeled it with a linear regression. The regressions were built using the *lm* function in *R*. Because the observations within each study are not independent, we tested our coefficients using the *HC1* cluster-robust standard errors implemented in the package *sandwich* (Zeileis, 2004; Zeileis & Graham, 2020). Hypothesis testing of our coefficients was computed using the *coeftest* function of *lmtest* (Zeileis & Hothorn, 2002).

Considering that the value of 0 is not meaningful for either of our independent variables, the models were fit on *Z*-scores. Overall R^2 values for the models were obtained using the *rsq* package, (Zhang, 2022).

To test the effects of both ambient frequency and articulatory complexity, we fitted three models for each language: one model including only frequency, one including only complexity, and one including both. We did not have a set prediction for the interaction between both variables, so we did not include an interaction term.

Results

Table 2 highlights the relationship between our variables. For all four languages, consonants with higher frequency tend to have a lower age of acquisition than those with lower frequency (Figure 1). The linear models show that both frequency and AC are related to age of acquisition. Table 2 contains the coefficients and overall R^2 for these effects. All models including single variables have significant coefficients for *F* and *C* that go in the predicted direction: negative *F* coefficients and positive *C* coefficients.

The models containing both predictors for Spanish, Japanese, and Korean provide conflicting evidence about whether *F* and *C* explain different sources of variance. Although the R^2 for the combined model is slightly higher in all three cases, the difference is very small. However, for Spanish, Japanese and Korean, the individual coefficients of the effects go in the predicted direction. Moreover, the contribution of *F* over *C* is significant in the first two, and close to significance (t = -1.66) in Korean (which is the language with the fewest studies and consonants).

Table 2. Coefficients and test statistics for all models of the four languages in the study.

	Model	Term	Coef	SE	t	p	R^2
Eng	$A \sim F$						0.07
		F	-0.63	0.10	-6.1	<0.05	
	$A \sim C$						0.36
		C	1.23	0.14	8.7	<0.05	
	$A \sim F + C$						0.37
		F	0.22	0.10	2.3	<0.05	
		C	1.33	0.16	8.4	< 0.05	
Spa	$A \sim F$						0.07
		F	-0.66	0.15	-4.5	<0.05	
	$A \sim C$						0.17
		C	1.01	0.10	10.0	<0.05	
	$A \sim F + C$						0.18
		F	-0.30	0.13	-2.3	<0.05	
		C	0.88	0.06	14.8	<0.05	
Jpn	$A \sim F$						0.11
		F	-0.78	0.14	-5.7	<0.05	
	$A \sim C$						0.19
		C	0.84	0.08	10.5	<0.05	
	$A \sim F + C$						0.21
		F	-0.41	0.17	-2.4	<0.05	
		C	0.69	0.12	5.7	<0.05	
Kor	$A \sim F$						0.07
		F	-0.56	0.25	-2.3	<0.05	
	$A \sim C$						0.10
		C	0.62	0.19	3.2	<0.05	
	$A \sim F + C$						0.13
		F	-0.51	0.25	-1.7	>0.05	
		C	0.52	0.19	2.8	<0.05	

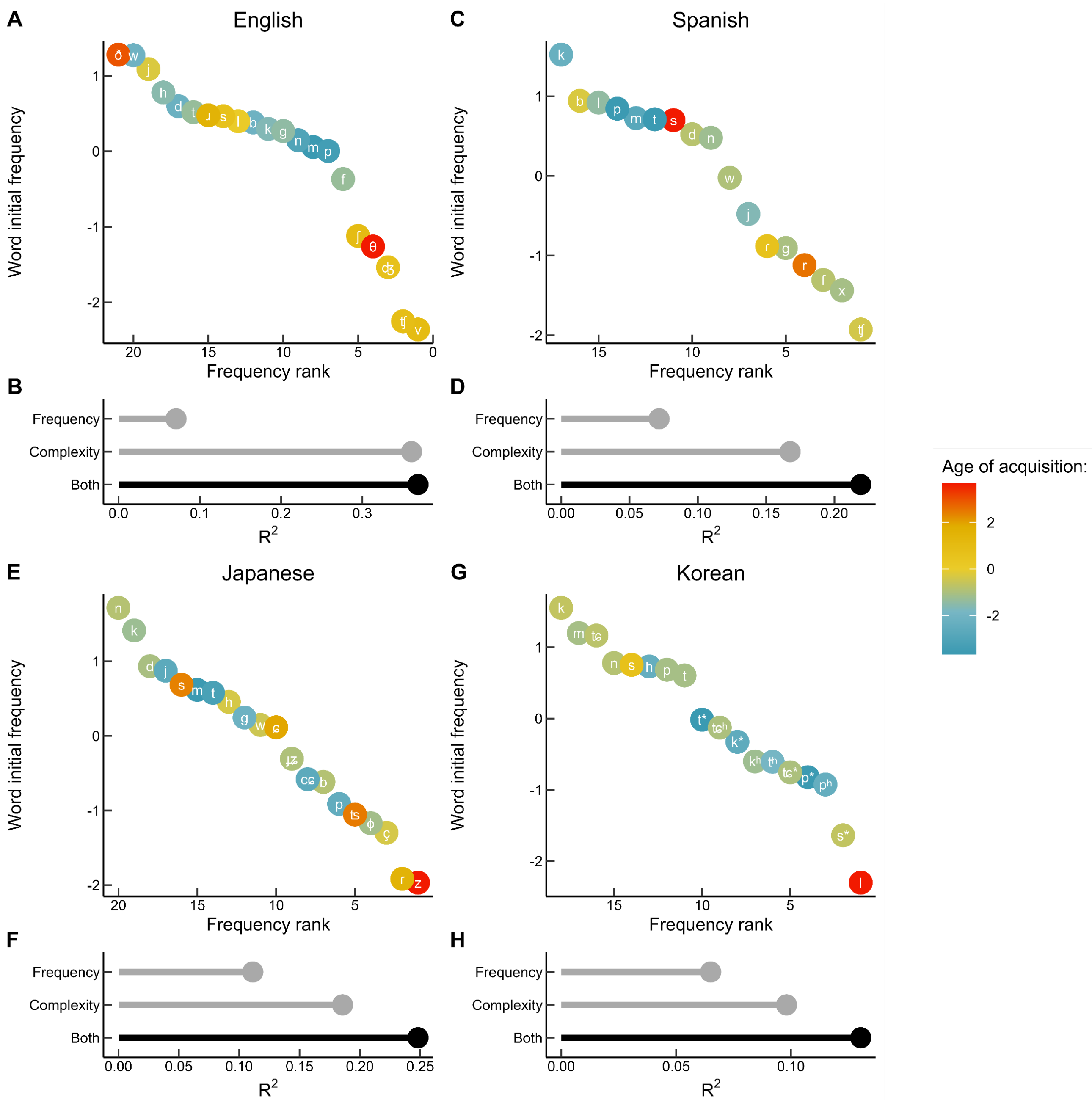

Figure 1. Relationship between word-initial frequency, articulatory complexity, and age of acquisition. **A**, **C**, **E** and **G** show, on the *y*-axis, the mean log-transformed within-corpus consonant frequency per million tokens for each consonant, and, on the *x*-axis, the rank of this same variable. The color of each dot represents the logit-transformed age, which is the dependent variable of the regressions. Each language is shown separately. Warmer colors indicate consonants that are learned later in development. Below them, **B**, **D**, **F**, and **H** show the R^2 of the three different linear models with the logit transformation of the within-study min-max normalized age of acquisition of each consonant, the natural logarithm of the frequency per million tokens averaged across corpora, articulatory complexity, and both as the independent variable.

The case of English is more complicated due to Kent's (1992) goal when positing the articulation categories: explaining their age of acquisition (see the Introduction and the Discussion). Thus, there is little variance for the frequency of a consonant to explain once Kent's categories of articulatory complexity have been included in the model. This issue makes an interpretation of the coefficient of *F* difficult and its significance possibly artifactual.

Discussion

Our measures take advantage of the largest data sets available for both consonant learning trajectories and regularities of children's linguistic environment. For all the languages under study, the frequency with which a consonant is present in children's language environment is significantly related to the age children acquire that consonant and it explains a considerable amount of variance. This relation is in the expected direction for all four languages considered.

Importantly, these two variables have a considerably different origin and level of sophistication. On the one hand, articulatory complexity is notoriously difficult to measure, and is typically an expert-crafted variable. In Kent (1992), articulatory complexity categories were originally derived from English age of acquisition data itself, and supported by high-level descriptions of the movements of the articulators necessary for adult-like proficiency with a specific consonant. In contrast, our consonant frequency measure is a basic, low-level statistic of the language environment that was computed bottom-up from a large amount of readily available data. Thus, considering its simplicity, we consider these results to be evidence of the strong promise of studying the effects of environmental statistics on phonological acquisition. Moreover, our results are completely consistent with the core of statistical learning: language acquisition, in this case consonant learning, is a product of both biological constraints and the detectable probabilistic patterns of the environment.

The origin of the articulatory complexity categories is a noteworthy limitation of our study. Kent explicitly acknowledges that the categories he designed for English are *based on* age of acquisition[2]. Although this is, of course, a reasonable strategy, it does mean that, in our analyses of English, articulatory complexity acts as a post-hoc construct that leaves no variance for ambient consonant frequency to explain. And, although these categories have been used in other studies of ambient frequency effects on consonant acquisition (Stokes & Surendran, 2005; Cychosz, 2017), it is difficult to interpret how AC and frequency might interact during the process of consonant acquisition for English. Moreover, this measure of AC introduces an important confound when included in the other languages: it is hard to parse out whether its explained variance comes from genuinely capturing a cross-linguistically relevant measure of articulatory difficulty, or the similarities between the statistics of each language and English. Therefore, a more data-driven measure of the difficulty of each consonant is needed to really assess the hypotheses.

One promising measure of AC in the future comes in the form of tongue movement ultrasound, which captures low-level motor data on the ballistic movements of the articulators during real-time consonant production (Kabakoff et al., 2022). By obtaining tongue ultrasound measures of children's consonant articulation, future studies can utilize measures of articulatory complexity. Computational approaches are also possible through simulating the muscle movements required to produce different sounds (see Blasi et al., 2019). However, both of these approaches are largely at a programmatic stage, and measures of the consonants we used, especially other than English, are not readily available.

Another limitation of the study is that we focused on group-level data, which does not allow for predicting individual differences in consonant trajectories. Future studies based on our results could design investigations to better understand the underlying processes which give rise to variation in how individual children learn to produce the speech sounds of their ambient language.

The promise shown in this study by measuring cross-linguistic consonant patterns in children's language environment suggests a productive research program to further unpack regularities that are likely to guide how children learn to talk. The statistical learning perspective on language acquisition makes the prediction that children are sensitive to low- and high-level regularities and detectable patterns in the input which influence how learning proceeds (Saffran, 2020). This process is constrained by biological and cognitive factors. To continue exploring the potential effects of low-level ambient consonant features on consonant learning, future studies can investigate consonant frequencies beyond the word-initial position and consider, for example, word-level stress patterns. Moreover, other high-level probabilistic features of consonants, such as their functional load (i.e., the extent to which consonant contrasts distinguish words in a given lexicon; Stokes & Surendran, 2005) and perceptual salience can be investigated as complements to more basic frequency patterns. Finally, future work will assess differences in the extent to which consonants are experienced within a socially interactive contexts, scenarios which are known to modulate children's attention and vocal learning (Elmlinger et al., 2023; Goldstein & Schwade, 2008).

More generally, this study fits within a broader field effort to evaluate hypotheses about language development from a more cross-linguistically and ecologically valid perspective (Christiansen et al., 2022; Kidd & Garcia, 2022). Although the mere existence of cross-linguistic variation in the itinerary of consonant acquisition is not an absolute proof against a hypothesis based purely on articulatory complexity,

[2] According to Kent, the complexity categories are an interpretation of the "motoric adjustments" that underly "four developmental sets of sounds" (Kent, 1992, p. 74).

comparative research is able provide more detailed insights on the specific mechanisms that drive acquisition processes (Christiansen et al., 2022). The evidence presented is a first approximation at such a study, assessing the influence of different environmental and biological features on consonant acquisition in a cross-linguistic comparative context. However, the languages used in the study vary in too many dimensions and are too few, weakening the conclusions that can be drawn from it. Therefore, and most importantly, future work will examine a broader sample of languages and consider fine-grained, controlled comparisons between closely related languages to better pry apart and understand the interweaving influence of environmental and biological constraints on consonant acquisition.

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