

Measuring Children’s Early Vocabulary in Low-Resource Languages Using a Swadesh-style Word List

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Abstract

Early language skill is predictive of later life outcomes, and is thus of great interest to developmental psychologists and clinicians. The Communicative Development Inventories (CDI), including a parent-reported inventory of early-learned vocabulary items, have proven to be valid and reliable instruments for measuring children’s early language skill. CDIs have been painstakingly adapted to dozens of languages, and cross-linguistic comparisons thus far show both consistency and variability in language acquisition trajectories. However, thousands of languages do not yet have CDIs, posing a significant barrier to increasing the diversity of languages that are studied. Here, we propose a method for selecting candidate words to include on new CDIs, leveraging analysis of psychometric properties of translation-equivalent concepts that are frequently included on existing CDIs. Leveraging 26 datasets from existing CDIs, we propose a list of 229 concepts that have low variability in their cross-linguistic learning difficulty. This pool of common concepts— analogous to the “Swadesh” lists used in glottochronology—can be used as a starting point for future CDI adaptations. We test how well the proposed list generalizes to data from 8 additional languages.

Keywords: early language learning; CDI; psychometrics; cross-linguistic comparison; Swadesh vocabulary

Introduction

Tools that enable valid assessments of children’s early language abilities are invaluable for researchers, clinicians and parents, as early language skill is predictive of educational outcomes years later (e.g., Bleses, Makransky, Dale, Højen, & Ari, 2016). The MacArthur-Bates Communicative Development Inventories [CDIs; Fenson et al. (2007); Marchman, Dale, & Fenson (2023)] are parent report assessments that provide reliable and valid estimates of children’s early vocabulary size and other aspects of early communicative development, such as use of gestures and of word combinations. Parent report is a relatively quick and low-cost method to assess early language skills since it takes advantage of the fact that parents are “natural observers” of their child’s skills and does not depend on a child engaging with an (unfamiliar) experimenter.

Over the years, the CDIs have been adapted to dozens of languages, with forms now available in English, Spanish, French, Hebrew, and Mandarin, to name just a few. Recently, data from more than 85,000 CDIs in 38 languages have been archived in a central repository [Wordbank; Frank, Braginsky, Yurovsky, & Marchman (2017)]. These data have revealed both cross-linguistic consistency and variability in early lan-

guage skills, with insights from these patterns informing theories of early language learning (Frank, Braginsky, Yurovsky, & Marchman, 2021). For example, cross-linguistic analyses indicate that measures of vocabulary size are tightly correlated with other aspects of early language skill, like gesture and grammatical competence. Thus, over development, the language system is “tightly woven” (Bates et al., 1994; Frank et al., 2021) and early vocabulary size serves as a good proxy measure of children’s overall language skill.

On the CDIs, vocabulary size is assessed via a checklist format, which enables caregivers to scan and recognize words their child produces or understands, rather than relying on recall alone. For example, the American English CDI Words & Sentences (CDI:WS) form, targeting children 16-30 months of age, is comprised of 680 words from 22 semantic categories, including nouns (e.g., Body Parts, Toys, and Clothing), action words, descriptive words, and closed-class words such as pronouns. The vocabulary checklist from the American English CDI Words & Gestures (CDI:WG) form, targeting younger children ages 8 to 18 months, is comprised of ~ 400 words from a similar set of categories. Items on these original forms were chosen to reflect a range of difficulty levels (i.e., easy, moderate, and more difficult), as well as capture the linguistic and societal contexts of (most) children living in the US. Short versions of each of these forms are also available, each with about 100 items (e.g., Fenson et al., 2000), consisting of a set of items that generate scores that more strongly correlate with scores on the long forms, while retaining representation across a broad set of semantic categories.

Creating a new CDI requires a lot of effort and resources, presenting a daunting barrier to increasing the diversity of languages studied. Following the guidelines¹ from the MacArthur-Bates CDI Advisory Board, the process of adapting a CDI for a language other than American English goes well beyond simply translating items on these forms to that new language. While the process can begin with identifying translation equivalents (i.e., items that capture the same general concept in both languages, e.g., “dog” in English, and “perro” in Spanish), the final item set must then be filtered so that all items appropriately reflect the linguistic and socio-cultural context of the children learning that language. This

¹<https://mb-cdi.stanford.edu/adaptations.htm>

process usually requires considerable time and effort by researchers who are both native speakers of the language and who have experience with children, to first select and identify translation equivalents and to then iteratively add, refine, and pilot the new CDI in the target language. Because the goal is to obtain the set of items that best capture general trends and individual differences in that language, the items across CDIs in different languages do not necessarily overlap to a great extent. For example, the American English CDI:WS and Mexican Spanish CDI:WS forms—two of the first CDIs created—each have 680 words, but only have 463 overlapping concepts (68%).

It is well-established that, all over the world, early-learned words reflect the people and things that children are likely to experience, that is, words for family members, animals, and common household objects (Frank et al., 2021; Tardif et al., 2008). Given this finding, it is reasonable to ask: Is there a single set of translation equivalents that would meet the criteria for inclusion on CDIs from multiple languages?

To facilitate this effort, it is useful to leverage Item-Response Theory (IRT, Embretson & Reise, 2013) models. IRT models infer both the abilities of test takers and the difficulty of individual test items (i.e., words), along standardized dimensions. Recent work using IRT models has facilitated our understanding of the psychometric properties of specific CDI instruments. As such, they offer the potential to not only yield more accurate measures of children’s language ability, but also to enable the construction of language-specific Computerized Adaptive Tests (CATs), which choose the next test item based on the responses to the previous items, and thus quickly hone in on the test taker’s language ability. CAT-based CDIs presenting 50 or fewer items have been found to strongly correlate with scores on the full CDI:WS (Chai, Lo, & Mayor, 2020; Makransky, Dale, Havmose, & Bleses, 2016; Mayor & Mani, 2019). A general method for creating CDI CATs that work well across a broader age range (12–36 months) has been proposed, and tested for American English and Mexican Spanish (Kachergis, Marchman, Dale, Manke-witz, & Frank, 2022). However, the IRT model driving each CAT needs to be trained on a large and normative dataset, which may not be available in a given language. To date, the IRT models are fitted separately for each language, and the fitted parameters (e.g., word difficulty) are likely to vary across languages.

The goal of the current study is to use IRT modeling in conjunction with data from Wordbank to examine whether there might be a core set of concepts that are frequently included on CDIs, and—importantly—whether enough of them are of roughly equal difficulty across many languages to allow them to be used as candidate items in new languages. This work takes its inspiration from the fields of lexicostatistics and glottochronology, where researchers (notably, Swadesh, 1971) have proposed lists of common concepts that exist in all catalogued languages, in order to quantify the genealogical relatedness and dates of divergence of languages. For exam-

ple, the original Swadesh list contains 100 words, comprised of categories including common pronouns (*I, you, we*), animals (*man, fish, bird, dog*), objects (*tree, leaf, sun, mountain*), and verbs (*die, see, sleep, kill*). Extending this work to the development of a universal CDI, or “Swadesh CDI,” would include many of the concepts that researchers have chosen to include on several CDI:WS adaptations, and which have relatively similar difficulty across many languages. If such a list were generalizable to other languages, it could serve as a helpful starting point for the development of new CDI adaptations, since the constituent words would already have good cross-linguistic difficulty estimates.

In particular, our contributions are 1) to revise and extend a set of translation-equivalent concepts in Wordbank, 2) to fit IRT models to 28 CDI:WS datasets, 3) evaluate 25 candidate lists of “Swadesh CDI” items from a cross-linguistic comparison of concept difficulty and inclusion, and 4) identified and characterized the most informative Swadesh CDI list of 229 concepts and tested its generalization to a set of eight additional low-data languages. Our full analysis, the Swadesh CDI list, and other information valuable for developing a new CDI are openly available on OSF. We end by making a concrete proposal for how this Swadesh CDI list could be used in creating future CDI adaptations, and by discussing the strengths and weaknesses of our approach.

Methods

Item Response Theory

A variety of IRT models targeting different types of testing scenarios have been proposed (see Baker, 2001 for an overview), but for the dichotomous responses that parents make for each item (word) regarding whether their child can produce a given word, we used the popular 2-parameter logistic (2PL) model that is best justified for CDI data out of four standard models (see Kachergis et al., 2022).

The 2PL model jointly estimates for each child j a latent ability θ_j (here, language skill), and for each item i two parameters: the item’s difficulty b_i and discrimination a_i , described below. In the 2PL model, the probability of child j producing a given item i is

$$P_i(x_i = 1 | b_i, a_i, \theta_j) = \frac{1}{1 + e^{-Da_i(\theta_j - b_i)}}$$

where D is a scaling parameter ($D = 1.702$) which makes the logistic more closely match the ogive function used in a standard factor analysis (Chalmers, 2012; Reckase, 2009). Children with high latent ability (θ) will be more likely to produce any given item than children with lower latent ability, and more difficult items will be produced by fewer children (at any given θ) than easier items. The discrimination (a_i) adjusts the slope of the logistic (in the classic 1-parameter logistic “1PL” model, the slope is always 1). Items with higher discrimination (i.e. slopes) better distinguish children above vs. below that item’s difficulty level, and hence are generally more useful. While other standard IRT models exist (e.g.,

the 3-parameter logistic model adds a “guessing” parameter for each test item), a recent study found the 2PL model most appropriate for multiple Wordbank datasets (Kachergis et al., 2022).

Datasets

Language	items	N
Norwegian	731	9304
English (American)	680	8828
Danish	725	3714
Portuguese (European)	639	3012
Turkish	711	2422
Spanish (Mexican)	680	2025
Mandarin (Taiwanese)	696	1897
English (Australian)	558	1520
French (French)	690	1410
Korean	641	1376
Cantonese	804	1295
German	588	1181
Slovak	609	1066
Mandarin (Beijing)	799	1056
Russian	728	1037
French (Quebecois)	664	929
Swedish	710	900
Spanish (Argentinian)	699	784
Italian	670	752
Spanish (European)	588	593
Hebrew	605	518
Latvian	723	500
Czech	553	493
Croatian	717	377
Hungarian	802	363
Dutch	704	303
Greek (Cypriot)	815	176
Spanish (Peruvian)	600	105
Kigirima	696	100
English (Irish)	660	99
Irish	691	99
Kiswahili	705	90
Finnish	581	70
Persian	558	50

Table 1: Number of CDI:WS items and subjects (N) per dataset. The final eight datasets were used for a generalization test.

We report IRT analyses for twenty-six languages from Wordbank (Frank et al., 2017), comprising production data from CDI:WS vocabulary checklists that have at least 200 administrations.² Data from the first twenty-six rows of Table 1 (Norwegian through Dutch) were used to select a pool of words with approximately equal cross-linguistic difficulty. CDI:WS production data from an additional eight languages (bottom of Table 1: Greek through Persian) had too few participants to be analyzed with IRT. Datasets for these languages were used to test how well the selected pool can be expected to generalize to new languages.

Uni-lemmas Comparison across languages requires a method to map between words that correspond to broadly

similar concepts across languages. As such, each item on the CDI:WS for each language was mapped onto a set of “universal lemmas” or “uni-lemmas”, which are approximate cross-linguistic conceptual mappings of words. For example, “chat” (French) and “gato” (Spanish) both correspond to the same uni-lemma, *cat*. These mappings were updated for this project to improve their quality and systematicity, and to increase coverage across items and languages. This new set of uni-lemmas was constructed based on glosses provided by the original contributors of the Wordbank datasets, which were then verified by native or advanced proficient speakers of the language, and cleaned to increase their consistency across languages. All uni-lemmas are accessible from Wordbank; details about the recent update can be found at <https://github.com/langcog/update-unilemmas>.

Participants The CDI:WS production dataset consists of the combined Wordbank production data for 48444 children aged 16–30 months on 23020 items across 34 forms. Note that the distributions of demographic variables (age, sex, maternal education, etc.) of these datasets are not matched, so comparing overall language ability estimates across languages would be ill-advised. (See Frank et al. (2021) for a discussion of effects of demographic variables on vocabulary development.) Thus, we focused only on the estimated item parameters, and in particular the variability of item difficulty (b_i).

Instruments When a CDI:WS forms was administered, caregivers were asked to indicate for each vocabulary item on the instrument whether or not their child can recognizably produce (say) the given word in an appropriate context.

“Produces” responses were coded as 1 and all other responses were coded as 0. Our datasets consisted of a dichotomous-valued response matrix for each language, of size N subjects \times W words. All models, data, and code for reproducing this paper are available on OSF³.

Results

Across the 26 IRT models for different CDI:WS forms, difficulty and discrimination parameters for a total of 23020 items were fitted. Of those items, 95% had uni-lemmas defined, with a median of 693 per CDI:WS form (range: 553 in Czech to 804 in Cantonese). A total of 1839 uni-lemmas were defined across the 26 CDI:WS forms, but 528 of these were singletons, appearing on only one of the 26 forms.⁴ Indeed, there was a significant relation between the number of times a uni-lemma appears and its difficulty: the more times a uni-lemma appears, the *easier* it tended to be ($r = -0.37$, $t(1837) = -17.15$, $p < .001$). Moreover, there was a weak but significant relation between the number of forms a uni-lemma appears on and its cross-linguistic vari-

³OSF repository: <https://osf.io/8swhb/>.

⁴These singletons were significantly more difficult than the 1311 uni-lemmas appearing more than once ($M_1 = 1.45$; $M_{>1} = 0.85$; $t(899) = 7.66$, $p < .001$).

²<http://wordbank.stanford.edu/contributors>

ability ($r = 0.17$, $t(1309) = 6.35$, $p < .001$). It is perhaps intuitive that lower-variability concepts tend to be the earlier-learned items which are already selected to be on more CDI forms, echoing prior work characterizing the consistency of children’s first words across several languages (Tardif et al., 2008). However, these modest but significant correlations were also important to keep in mind as we chose our Swadesh CDI candidates, as selecting too many easy items could result in older children being at ceiling.

Identifying Swadesh CDI Candidates The goal was to choose uni-lemmas with low variability in their cross-linguistic difficulty—that is, uni-lemmas that are similarly difficult to learn across languages. There were two thresholds that had to be defined to select Swadesh CDI (S-CDI) candidates: 1) k , the number of current CDI:WS forms a uni-lemma must appear on, and 2) v_{min} , the threshold for variability in cross-linguistic difficulty. For v_{min} , we simply considered the uni-lemmas with a variation in cross-linguistic difficulty that was half a standard deviation less than average, among the set of uni-lemmas that were on at least k forms. Assuming variability was normally-distributed, this criterion preserved the $\sim 19\%$ of the uni-lemmas with the lowest variability.

It was less clear how to choose k , the minimum number of forms a uni-lemma must appear on to be considered eligible. As reported above, the more forms a uni-lemma appeared on, the easier that concept tended to be, and the greater its cross-linguistic variability in difficulty ($SD(d)$) tended to be. Thus, the higher the threshold k , the more bias there would be toward the Swadesh candidates being easier than typical, as well as more variable in difficulty. Having a Swadesh CDI list that was much easier than the CDI:WS is undesirable, as it may show ceiling effects for older children, while selecting words that are more variable in difficulty may result in a test that generalizes less well to other languages. Of course, the higher k , the fewer uni-lemmas there were available to choose from: 1303 uni-lemmas appeared on 2 or more CDIs, but only 30 appeared on all 26 CDIs.

Because choosing k is difficult *a priori*, we opted to do a grid search across all possible values. For each k , we found the set of N uni-lemmas appearing k times on each form, calculated the mean and standard deviation of the difficulties of those items, and then identified the subset of those N items with $SD(d) < v_{min}$: these comprised the k^{th} Swadesh list, as shown in Figure 1 (top). For each candidate Swadesh list, we evaluated the total test information yielded by that Swadesh list for each of the 26 CDI:WS forms. Total test information was calculated as the integral across a range of test-taker abilities (here, $\theta \in \{-4, 4\}$) of the information yielded on a test, calculated using the IRT difficulty and discrimination parameters for those test items. Finding the k that yielded the highest total test information was the main objective (see online Appendix for details).

As shown in Figure 1 (bottom), test information was maximized with $k = 9$, and from these 1309 uni-lemmas appearing

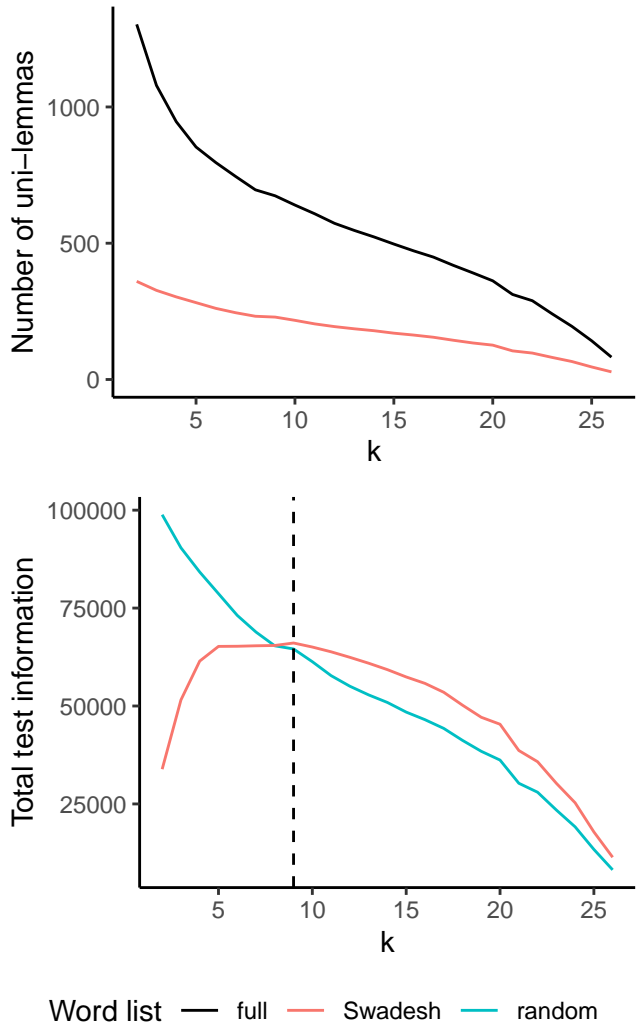


Figure 1: Number of uni-lemmas appearing on at least k lists (top). Total test information for Swadesh lists, and random tests of the same length (bottom).

on at least 9 forms, 229 Swadesh-CDI items were selected for having cross-linguistic variability below the threshold. The mean difficulty of the S-CDI items was also quite close to the difficulty of the other uni-lemmas that appeared on at least 9 forms ($M(d_{Swad}) = 0.31$; $M(d_{other}) = 0.36$), suggesting that the S-CDI items were fairly representative.

Characterizing the Swadesh-CDI

The 229 S-CDI items represented 21 of the 22 semantic categories present on the original American English CDI:WS form, with action words, animals, household, food/drink, body parts, and descriptive words being most prevalent, and connecting words, quantifiers, helping verbs, and articles being rare, and question words being unrepresented. 54% of the S-CDI concepts were nouns, 22% were predicates (verbs and adjectives), 17% were function words, and 7% belonged to other lexical categories. This breakdown was comparable

to the lexical category percentages on the 680-item English CDI:WS (46% nouns, 24% predicates, 15% function words, and 5% other), suggesting that the S-CDI list did not show a particular lexical category bias. The S-CDI items were also present on more forms than typical in the selection set: on average, each item appeared on 19 forms, despite only being required to appear on at least 9 forms. Finally, 28 S-CDI uni-lemmas were not present on the American English CDI:WS (e.g., *fruit*, *spider*, *enter*, *near*), suggesting that this method may help us move beyond an English-centric approach to studying early language.

Figure 2 shows the average cross-linguistic difficulty of CDI items by semantic category, for both Swadesh and non-Swadesh items. The difficulty of Swadesh items generally tracked with that of non-Swadesh items, although there were cases where one or the other was more or less difficult.

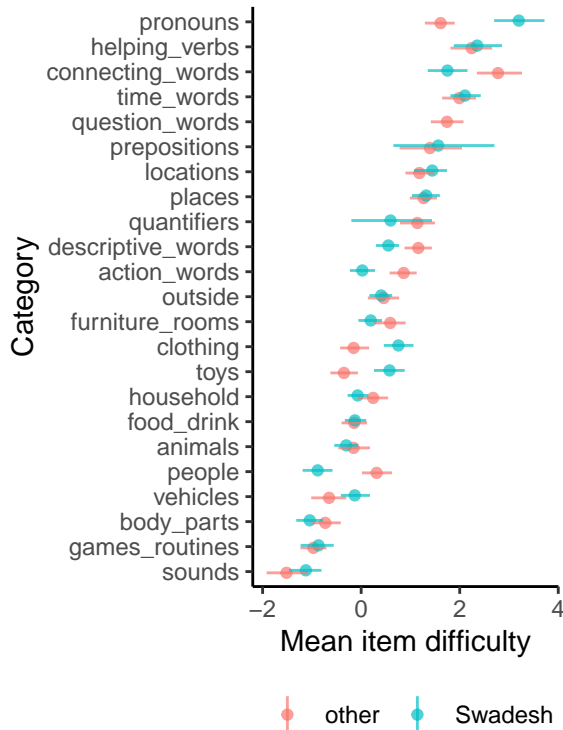


Figure 2: Mean cross-linguistic difficulty of CDI words by semantic category, showing that selection of Swadesh concepts broadly maintained representative difficulty. Bars represent bootstrapped 95% confidence intervals.

Comparing the IRT parameters of the S-CDI uni-lemmas to the rest of the items (across all CDI:WS forms) showed that the discrimination parameter (i.e., slope) of the Swadesh items did not significantly differ from the others, suggesting that the Swadesh items could measure ability as well as non-Swadesh uni-lemmas. However, the candidate Swadesh items were significantly easier than the other uni-lemmas (mean S-CDI $d = 0.11$, other items' mean $d = 0.53$, $t(8749) = -13.09$, $p < .001$).

Validating the Swadesh CDI

To validate the S-CDI, we first measured how well simulated raw scores from the S-CDI items correlated with full CDI:WS scores. This metric approximately reflects how reliable the S-CDI would be as a measure of a child's vocabulary. On average, for the 26 large CDI:WS datasets, the S-CDI's scores were strongly related to the full CDI:WS scores (mean $r = 0.990$; $min = 0.976$, $max = 0.996$; full table on OSF). We compared these correlations against two baselines, which were designed to simulate possible methods of sampling items for a hypothetical new CDI form. The first baseline was the "English uni-lemmas" baseline, in which uni-lemmas were randomly sampled from the uni-lemmas that appeared on the English (American) CDI:WS form. This baseline had a mean correlation to full CDI:WS scores of $r = 0.997$. The second baseline was the "random uni-lemmas" baseline, in which uni-lemmas were randomly sampled from the total set of unique uni-lemmas across all the 26 CDI:WS forms, weighted by the number of forms that each uni-lemma occurred on. This baseline had a mean correlation to full CDI:WS scores of $r = 0.997$.

Next, we measured the total test information yielded by the two baselines (recalling that total test information was one criterion for the construction of the S-CDI). This metric reflects how well the S-CDI would be able to differentiate the ability of children across different ability levels. As found above, the S-CDI yielded a mean total test information of 66085, whereas the English uni-lemmas baseline yielded a total test information of 67866, and the random uni-lemmas baseline yielded a total test information of 64504. Neither of these baselines significantly differed from the Swadesh CDI's total test information.

Testing Generalization of the Swadesh CDI

We then evaluated the S-CDI's performance in a test of generalization to eight more CDI:WS datasets. For the eight low-data languages, a comparison of simulated S-CDI scores to full CDI:WS revealed that the S-CDI's raw scores were again strongly related (mean $r = 0.990$; $min = 0.983$, $max = 0.997$). Table 2 shows the results of this comparison.

language	N	Rand r	Swadesh r
English (Irish)	161	0.995	0.990
Finnish	161	0.997	0.997
Greek (Cypriot)	142	0.994	0.987
Irish	160	0.995	0.988
Kigiriana	179	0.996	0.996
Kiswahili	179	0.996	0.992
Persian	103	0.987	0.983
Spanish (Peruvian)	141	0.996	0.991

Table 2: Generalization test results.

Actions (32)	fit, stay, lick, hear, like, sweep, swim, cry, catch, wait, knock, kick, tickle, clean, bite, paint, see, help, blow, sing, dance, draw, jump, fall, play, sleep, drink, eat, <i>enter, comb, poop, pee</i>
Animals (23)	turkey, deer, lamb, zebra, animal, cat, penguin, duck, squirrel, donkey, ant, bee, lion, chicken, monkey, cow, horse, dog, <i>chick, goat, spider, pigeon, hippopotamus</i>
Body Parts (17)	tongue, shoulder, lip, mouth, knee, eye, head, hand, nose, belly button, finger, tooth, chin, penis, vagina, <i>nail, back</i>
Clothing (8) Connectives	belt, zipper, shorts, necklace, dress, bib, button, <i>skirt</i> and, then
Descriptives (18)	first, better, stick, careful, black, white, green, yellow, blue, red, all gone, awake, heavy, hungry, dirty, cold, <i>sweet, strong</i>
Food/Drink (21)	pumpkin, hamburger, vitamin, nut, popcorn, soda, ice, salt, peas, lollipop, chips, French fries, orange, milk, chocolate, yogurt, candy, banana, <i>ham, honey, fruit</i>
Furniture/ Rooms (12)	basement, sink, garage, stove, drawer, TV, high chair, washing machine, refrigerator, door, bed, <i>mirror</i>
Games/Routines	yes, shh, breakfast, shopping, <i>good morning</i>
Helping verbs	try
Household (18)	nail, mop, camera, basket, radio, hammer, brush, broom, comb, towel, paper, toothbrush, glasses, key, telephone, spoon, <i>computer, toothpaste</i>
Locations (11)	in, under, out, behind, back, to, over, beside, <i>near, far, in front</i>
Outside (11)	cloud, sun, star, moon, sky, stick, sandbox, hose, snowman, ladder, lawn mower
People (10)	mommy, daddy, doctor, pet's name, child's name, police, mailman, clown, girl, babysitter's name
Places (7)	school, home, circus, movie, zoo, gas station, <i>market</i>
Pronouns	3PL.POSS, those, these
Quantifiers	a lot
Sounds (9)	meow, cockadoodledoo, grrr, choo choo, yum yum, quack quack, ouch, vroom, <i>tweet tweet</i>
Time Words	before, yesterday, tonight, today, later, tomorrow, now
Toys (5)	chalk, glue, play dough, toy, <i>pacifier</i>
Vehicles (6)	airplane, firetruck, helicopter, motorcycle, train, tricycle, <i>ambulance</i>

Figure 3: The 229 Swadesh CDI concepts by semantic category. Italicized items indicate concepts that are not included on the American English CDI:WS.

Discussion

This study compared psychometric models fitted to 26 CDI datasets in order to find concepts that had low variability in their cross-linguistic difficulty, and that were frequently included on CDI:WS forms. We identified 229 concepts that appeared on at least 9 of the CDIs, and which had more consistent cross-linguistic difficulty than other concepts appearing on multiple CDIs. Using real-data simulations, we showed that administering this set of Swadesh CDI items would generate scores that were strongly related to full CDI:WS scores, both for the original 26 datasets, and in a generalization test to eight low-data languages. Moreover, the Swadesh CDI items resulted in higher total test information than tests of the same length composed of uni-lemmas either randomly selected from English, or randomly selected from the original 26 datasets weighted by frequency of occurrence. The Swadesh CDI contains items with relatively good

difficulty estimates cross-linguistically, and in the absence of access to researchers who are familiar with relevant local cultures and concepts, they may serve as a rapid, simple means of approximating children's ability levels, even in the absence of a large norming dataset.

However, the Swadesh CDI items were also significantly easier than other items, meaning that older children may perform at ceiling if given only the Swadesh CDI items. (This may be unsurprising from the perspective that Swadesh words are meant to be universal, and are therefore more frequent and basic—both within and across individual children's experiences.) Thus, our suggested use case for the Swadesh CDI list is as a starting point for researchers seeking to develop a CDI in a new language, rather than as a complete short-form CDI based on existing long-form CDI data. In particular, researchers should seek to add contextually appropriate items from the categories that were less well-represented on the Swadesh list, including question words, quantifiers, helping verbs, and pronouns. These categories also tended to be more difficult, so adding items from them will likely increase the difficulty ceiling of the form.

Another potential limitation of this work is that most existing CDIs (and most datasets available in Wordbank) target languages in the Indo-European language family. It is not clear to what extent this bias in the existing data might interfere with generalizing to non-Indo-European languages. Nonetheless, our original 26 datasets include 7 non-Indo-European languages (3 Sino-Tibetan, 1 Afro-Asiatic, 1 Uralic, 1 Koreanic, 1 Turkic), and the generalization datasets include 1 Uralic and 2 Niger-Congo languages (a language family not represented in the original datasets); the broad consistency across language families thus suggests that the effectiveness of the Swadesh list may be sufficiently robust.

Developing a list of appropriate vocabulary words is not the only challenge researchers face when seeking to develop and use parent-report measures in a new language and culture. The pragmatics of language between children and adults can differ greatly across cultures, and has been found to interfere with administration of parent-report measures of early vocabulary, for example in Kiswahili (Alcock, 2017) and Wolof (Weber, Marchman, Diop, & Fernald, 2018). As such, local cultural knowledge remains essential in appropriately developing and administering novel CDI adaptations.

Despite the myriad challenges that remain in creating new measures of early language development, we believe that the proposed Swadesh CDI list will give researchers a solid foundation to start from, lowering the barrier to the adaptation of CDI forms in new languages, since these are often time-consuming and challenging to construct. Expanding the number of languages with effective vocabulary measures would be a critical step in addressing issues related to the underrepresentation of linguistic diversity in language acquisition research (Kidd & Garcia, 2022). Certainly, increasing the diversity of languages studied is a critical step towards developing a truly general understanding of how young children

learn language.

Acknowledgements

Redacted for anonymous review.

References

- 10 Alcock, K. J. (2017). Production is only half the story—first words in two East African languages. *Frontiers in Psychology*, 8, 1898.
- Baker, F. B. (2001). *The basics of item response theory*. ERIC.
- Bates, E., Marchman, V., Thal, D., Fenson, L., Dale, P. S., Reznick, J. S., ... Hartung, J. (1994). Developmental and stylistic variation in the composition of early vocabulary. *Journal of Child Language*, 21(1), 85–123.
- Bleses, D., Makranksy, G., Dale, P. S., Højen, A., & Ari, B. A. (2016). Early productive vocabulary predicts academic achievement 10 years later. *Applied Psycholinguistics*, 37(6), 1461–1476.
- Chai, J. H., Lo, C. H., & Mayor, J. (2020). A Bayesian-inspired item response theory-based framework to produce very short versions of MacArthur-Bates Communicative Development Inventories. *Journal of Speech, Language, and Hearing Research*, 63(10), 3488–3500.
- Chalmers, R. P. (2012). mirt: A multidimensional item response theory package for the R environment. *Journal of Statistical Software*, 48(6), 1–29. <http://doi.org/10.18637/jss.v048.i06>
- Embretson, S. E., & Reise, S. P. (2013). *Item response theory*. Psychology Press.
- Fenson, L., Marchman, V. A., Thal, D. J., Dale, P. S., Reznick, J. S., & Bates, E. (2007). *MacArthur-Bates Communicative Development Inventories: User's guide and technical manual (2nd ed.)*. Baltimore, MD: Brookes.
- Fenson, L., Pethick, S., Renda, C., Cox, J. L., Dale, P. S., & Reznick, J. S. (2000). Short-form versions of the MacArthur Communicative Development Inventories, 21, 95–116.
- Frank, M. C., Braginsky, M., Yurovsky, D., & Marchman, V. A. (2017). Wordbank: An open repository for developmental vocabulary data. *Journal of Child Language*, 44(3), 677.
- Frank, M. C., Braginsky, M., Yurovsky, D., & Marchman, V. A. (2021). *Variability and consistency in early language learning: The Wordbank project*. MIT Press.
- Kachergis, G., Marchman, V. A., Dale, P. S., Mankewitz, J., & Frank, M. C. (2022). Online computerized adaptive tests of children's vocabulary development in English and Mexican Spanish. *Journal of Speech, Language, and Hearing Research*, 65(6), 2288–2308.
- Kidd, E., & Garcia, R. (2022). How diverse is child language acquisition research? *First Language*, 42(6), 703–735. <http://doi.org/10.1177/01427237211066405>
- Makranksy, G., Dale, P. S., Havmose, P., & Bleses, D. (2016). An item response theory-based, computerized adaptive testing version of the MacArthur-Bates Communicative Development Inventory: Words & Sentences (CDI:WS). *Journal of Speech, Language, and Hearing Research*, 59(2), 281–289.
- Marchman, V. A., Dale, P. S., & Fenson, L. (2023). *MacArthur-bates communicative development inventories user's guide and technical manual, 3rd edition*. Baltimore, MD: Brookes Publishing Co.
- Mayor, J., & Mani, N. (2019). A short version of the MacArthur-Bates Communicative Development Inventories with high validity. *Behavior Research Methods*, 51(5), 2248–2255.
- Reckase, M. D. (2009). Multidimensional item response theory models. In *Multidimensional item response theory* (pp. 79–112). Springer.
- Swadesh, M. (1971). *The origin and diversification of language*. (J. Sherzer, Ed.). Chicago, IL: Aldine.
- Tardif, T., Fletcher, P., Liang, W., Zhang, Z., Kaciroti, N., & Marchman, V. A. (2008). Baby's first 10 words. *Developmental Psychology*, 44(4), 929.
- Weber, A. M., Marchman, V. A., Diop, Y., & Fernald, A. (2018). Validity of caregiver-report measures of language skill for Wolof-learning infants and toddlers living in rural african villages. *Journal of Child Language*, 45(4), 939–958. <http://doi.org/10.1017/S0305000917000605>