

¹ Peekbank: An open, large-scale repository for developmental eye-tracking data of children's
² word recognition

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25 **Open Practices Statement.** All code for reproducing the paper is available at
26 <https://github.com/langcog/peekbank-paper>. Raw and standardized datasets are available
27 on the Peekbank OSF repository (<https://osf.io/pr6wu/>) and can be accessed using the
28 peekbankr R package (<https://github.com/langcog/peekbankr>).

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37

Abstract

38 The ability to rapidly recognize words and link them to referents is central to children's
39 early language development. This ability, often called word recognition in the developmental
40 literature, is typically studied in the looking-while-listening paradigm, which measures
41 infants' fixation on a target object (vs. a distractor) after hearing a target label. We present
42 a large-scale, open database of infant and toddler eye-tracking data from
43 looking-while-listening tasks. The goal of this effort is to address theoretical and
44 methodological challenges in measuring vocabulary development. We first present how we
45 created the database, its features and structure, and associated tools for processing and
46 accessing infant eye-tracking datasets. Using these tools, we then work through two
47 illustrative examples to show how researchers can use Peekbank to interrogate theoretical
48 and methodological questions about children's developing word recognition ability.

49 *Keywords:* word recognition; eye-tracking; vocabulary development;
50 looking-while-listening; visual world paradigm; lexical processing

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53 word recognition

54 Across their first years of life, children learn words at an accelerating pace (Frank,
55 Braginsky, Yurovsky, & Marchman, 2021). While many children will only produce their first
56 word at around one year of age, most children show signs of understanding many common
57 nouns (e.g., *mommy*) and phrases (e.g., *Let's go bye-bye!*) much earlier in development
58 (Bergelson & Swingley, 2012, 2013; Tincoff & Jusczyk, 1999). Although early word
59 understanding is a critical element of first language learning, the processes involved are less
60 directly apparent in children's behaviors and are less accessible to observation than
61 developments in speech production (Fernald, Zangl, Portillo, & Marchman, 2008;
62 Hirsh-Pasek, Cauley, Golinkoff, & Gordon, 1987). To understand a spoken word, children
63 must process the incoming auditory signal and link that signal to relevant meanings – a
64 process often referred to as word recognition. One of the primary means of measuring word
65 recognition in young infants is using eye-tracking techniques that gauge where children look
66 in response to linguistic stimuli (Fernald, Zangl, Portillo, & Marchman, 2008). The logic of
67 these methods is that if, upon hearing a word, a child preferentially looks at a target
68 stimulus rather than a distractor, the child is able to recognize the word and activate its
69 meaning during real-time language processing. Measuring early word recognition offers
70 insight into children's early word representations: children's speed of response (i.e., moving
71 their eyes; turning their heads) to the unfolding speech signal can reveal children's level of
72 comprehension (Bergelson, 2020; Fernald, Pinto, Swingley, Weinberg, & McRoberts, 1998).
73 Word recognition skills are also thought to build a foundation for children's subsequent
74 language development. Past research has found that early word recognition efficiency is
75 predictive of later linguistic and general cognitive outcomes (Bleses, Makransky, Dale, Højlen,
76 & Ari, 2016; Marchman et al., 2018).

77 While word recognition is a central part of children's language development, mapping

78 the trajectory of word recognition skills has remained elusive. Studies investigating children's
79 word recognition are typically limited in scope to experiments in individual labs involving
80 small samples tested on a handful of items. The limitations of single datasets makes it
81 difficult to understand developmental changes in children's word knowledge at a broad scale.

82 One way to overcome this challenge is to compile existing datasets into a large-scale
83 database in order to expand the scope of research questions that can be asked about the
84 development of word recognition abilities. This strategy capitalizes on the fact that the
85 looking-while-listening paradigm is widely used, and vast amounts of data have been
86 collected across labs on infants' word recognition over the past 35 years (Golinkoff, Ma, Song,
87 & Hirsh-Pasek, 2013). Such datasets have largely remained isolated from one another, but
88 once combined, they have the potential to offer general insights into lexical development.

89 There has been a long history of efforts to aggregate data in a unified format in
90 developmental and cognitive psychology, generating projects that have often had a
91 tremendous impact on the field. Prominent examples in language research include the
92 English Lexicon Project, which provides an open repository of psycholinguistic data for over
93 80,000 English words and non-words in order to support large-scale investigations of lexical
94 processing (Balota et al., 2007); the Child Language Data Exchange System (CHILDES),
95 which has played an instrumental role in the study of early language environments by
96 systematizing and aggregating data from naturalistic child-caregiver language interactions
97 (MacWhinney, 2000); and WordBank, which aggregated data from the MacArthur-Bates
98 Communicative Development Inventory, a parent-report measure of child vocabulary, to
99 deliver new insights into cross-linguistic patterns and variability in vocabulary development
100 (Frank, Braginsky, Yurovsky, & Marchman, 2017, 2021).

101 In this paper, we introduce *Peekbank*, an open database of infant and toddler
102 eye-tracking data aimed at facilitating the study of developmental changes in children's word
103 recognition.

¹⁰⁴ **Measuring Word Recognition: The Looking-While-Listening Paradigm**

¹⁰⁵ Word recognition is traditionally studied in the looking-while-listening paradigm
¹⁰⁶ (Fernald, Zangl, Portillo, & Marchman, 2008; alternatively referred to as the intermodal
¹⁰⁷ preferential looking procedure, Hirsh-Pasek, Cauley, Golinkoff, & Gordon, 1987). In these
¹⁰⁸ studies, infants listen to a sentence prompting a specific referent (e.g., *Look at the dog!*)
¹⁰⁹ while viewing two images on the screen (e.g., an image of a dog – the target image – and an
¹¹⁰ image of a bird – the distractor image). Infants' word recognition is evaluated by how
¹¹¹ quickly and accurately they fixate on the target image after hearing its label. Past research
¹¹² has used this basic method to study a wide range of questions in language development. For
¹¹³ example, the looking-while-listening paradigm has been used to investigate early noun
¹¹⁴ knowledge, phonological representations of words, prediction during language processing, and
¹¹⁵ individual differences in language development (Bergelson & Swingley, 2012; Golinkoff, Ma,
¹¹⁶ Song, & Hirsh-Pasek, 2013; Lew-Williams & Fernald, 2007; Marchman et al., 2018; Swingley
¹¹⁷ & Aslin, 2002).

¹¹⁸ While this research has been fruitful in advancing understanding of early word
¹¹⁹ knowledge, fundamental questions remain. One central question is how to accurately capture
¹²⁰ developmental change in the speed and accuracy of word recognition. There is ample
¹²¹ evidence demonstrating that infants become faster and more accurate in word recognition
¹²² over the first few years of life (e.g., Fernald, Pinto, Swingley, Weinberg, & McRoberts, 1998).
¹²³ However, precisely measuring developmental increases in the speed and accuracy of word
¹²⁴ recognition remains challenging due to the difficulty of distinguishing developmental changes
¹²⁵ in word recognition skill from changes in knowledge of specific words. This problem is
¹²⁶ particularly thorny in studies with young children, since the number of items that can be
¹²⁷ tested within a single session is limited and items must be selected in an age-appropriate
¹²⁸ manner (Peter et al., 2019). More broadly, key differences in the design choices (e.g., how
¹²⁹ distractor items are selected) and analytic decisions (e.g., how the analysis window is defined)

130 between studies can obscure developmental change if not appropriately taken into account.

131 One approach to addressing these challenges is to conduct meta-analyses aggregating
132 effects across studies while testing for heterogeneity due to researcher choices (Bergmann et
133 al., 2018; Lewis et al., 2016). However, meta-analyses typically lack the granularity to
134 estimate participant-level and item-level variation or to model behavior beyond
135 coarse-grained effect size estimates. An alternative way to approach this challenge is to
136 aggregate trial-level data from smaller studies measuring word recognition with a wide range
137 of items and design choices into a large-scale dataset that can be analyzed using a unified
138 modeling approach. A sufficiently large dataset would allow researchers to estimate
139 developmental change in word recognition speed and accuracy while generalizing across
140 changes related to specific words or the design features of particular studies.

141 A related open theoretical question is understanding changes in children's word
142 recognition at the level of individual items. Looking-while-listening studies have been limited
143 in their ability to assess the development of specific words. One limitation is that studies
144 typically test only a small number of trials for each item, reducing power to precisely measure
145 the development of word-specific accuracy (DeBolt, Rhemtulla, & Oakes, 2020). A second
146 limitation is that target stimuli are often yoked with a narrow set of distractor stimuli (i.e., a
147 child sees a target with only one or two distractor stimuli over the course of an experiment),
148 leaving ambiguous whether accurate looking to a particular target word can be attributed to
149 children's recognition of the target word or their knowledge about the distractor.
150 Aggregating across many looking-while-listening studies has the potential to meet these
151 challenges by increasing the number of observations for specific items at different ages and by
152 increasing the size of the inventory of distractor stimuli that co-occur with each target.

153 **Replicability and Reproducibility**

154 A core challenge facing psychology in general, and the study of infant development in
155 particular, are threats to the replicability and reproducibility of core empirical results (Frank
156 et al., 2017; Nosek et al., 2022). In infant research, many studies are not adequately powered
157 to detect the main effects of interest (Bergmann et al., 2018). This issue is compounded by
158 low reliability in infant measures, often due to limits on the number of trials that can be
159 collected from an individual infant in an experimental session (Byers-Heinlein, Bergmann, &
160 Savalei, 2021). One hurdle to improving power in infant research is that it can be difficult to
161 develop a priori estimates of effect sizes and how specific design decisions (e.g., the number
162 of test trials) will impact power and reliability. Large-scale databases of infant behavior can
163 aid researchers in their decision-making by allowing them to directly test how different
164 design decisions affect power and reliability. For example, if a researcher is interested in
165 understanding how the number of test trials could impact the power and reliability of their
166 looking-while-listening design, a large-scale infant eye-tracking database would allow them to
167 simulate possible outcomes across a range of test trials, providing the basis for data-driven
168 design decisions.

169 In addition to threats to replicability, the field of infant development also faces
170 concerns about analytic reproducibility – the ability for researchers to arrive at the same
171 analytic conclusion reported in the original research article, given the same dataset. A recent
172 estimate based on studies published in a prominent cognitive science journal suggests that
173 analyses can remain difficult to reproduce, even when data are made available to other
174 research teams (Hardwicke et al., 2018). Aggregating data in centralized databases can aid
175 in improving reproducibility in several ways. First, building a large-scale database requires
176 defining a standardized data specification. Recent examples include the `brain imaging`
177 `data structure` (BIDS), an effort to specify a unified data format for neuroimaging
178 experiments (Gorgolewski et al., 2016), and the data formats associated with `ChildProject`,

179 for managing long-form at-home language recordings (Gautheron, Rochat, & Cristia, 2021).
180 Defining a data standard – in this case, for infant eye-tracking experiments – supports
181 reproducibility by guaranteeing that critical information will be available in openly shared
182 data and by making it easier for different research teams to understand the data structure.
183 Second, open databases make it easy for researchers to generate open and reproducible
184 analytic pipelines, both for individual studies and for analyses aggregating across datasets.
185 Creating open analytic pipelines across many datasets also serves a pedagogical purpose,
186 providing teaching examples illustrating how to implement analytic techniques used in
187 influential studies and how to conduct reproducible analyses with infant eye-tracking data.

188 **Peekbank: An open database of developmental eye-tracking studies.**

189 What all of these open challenges share is that they are difficult to address at the scale
190 of a single research lab or in a single study. To address this challenge, we developed
191 *Peekbank*, a flexible and reproducible interface to an open database of developmental
192 eye-tracking studies. The Peekbank project (a) collects a large set of eye-tracking datasets
193 on children’s word recognition, (b) introduces a data format and processing tools for
194 standardizing eye-tracking data across heterogeneous data sources, and (c) provides an
195 interface for accessing and analyzing the database. In the current paper, we introduce the
196 key components of the project and give an overview of the existing database. We then
197 provide two worked examples of how researchers can use Peekbank. In the first, we examine
198 a classic result in the word recognition literature, and in the second we aggregate data across
199 studies to investigate developmental trends in the recognition of individual words.

200 **Design and Technical Approach**

201 **Database Framework**

202 One of the main challenges in compiling a large-scale eye-tracking database is the lack
203 of a shared data format: both labs and individual experiments can record their results in a
204 wide range of formats. For example, different experiments encode trial-level and
205 participant-level information in many different ways. Therefore, we have developed a
206 common tabular format to support analyses of all studies simultaneously.

207 As illustrated in Figure 1, the Peekbank framework consists of four main components:
208 (1) a set of tools to *convert* eye-tracking datasets into a unified format, (2) a relational
209 database populated with data in this unified format, (3) a set of tools to *retrieve* data from
210 this database, and (4) a web app (using the Shiny framework) for visualizing the data. These
211 components are supported by three packages. The `peekds` package (for the R language, R
212 Core Team, 2021) helps researchers convert existing datasets to use the standardized format
213 of the database. The `peekbank` module (Python) creates a database with the relational
214 schema and populates it with the standardized datasets produced by `peekds`. The database
215 is served through MySQL, an industry standard relational database server, which may be
216 accessed by a variety of programming languages, and can be hosted on one machine and
217 accessed by many others over the Internet. As is common in relational databases, records of
218 similar types (e.g., participants, trials, experiments, coded looks at each timepoint) are
219 grouped into tables, and records of various types are linked through numeric identifiers. The
220 `peekbankr` package (R) provides an application programming interface, or API, that offers
221 high-level abstractions for accessing the tabular data stored in Peekbank. Most users will
222 access data through this final package, in which case the details of data formatting,
223 processing, and the specifics of connecting to the database are abstracted away from the user.

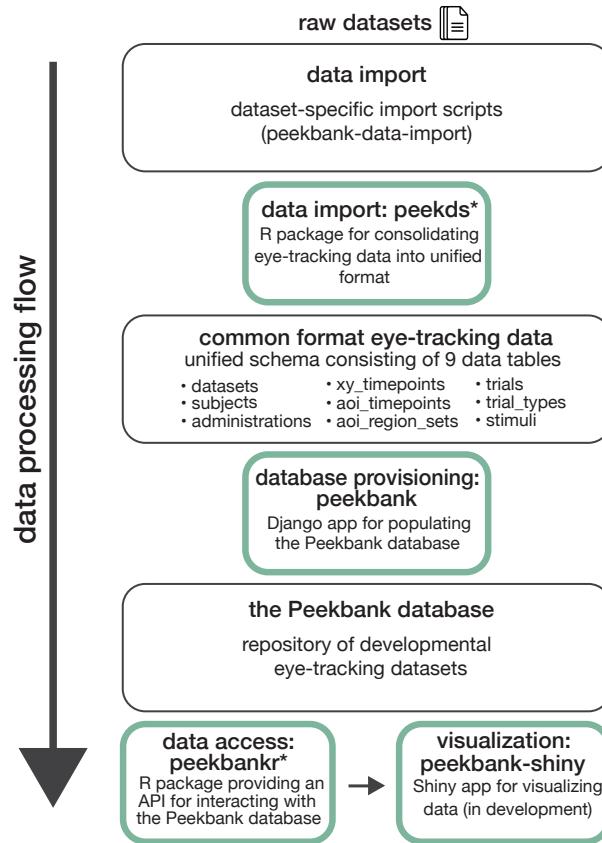


Figure 1. Overview of the Peekbank data ecosystem. Peekbank tools are highlighted in green. * indicates R packages introduced in this work.

224 Database Schema

225 The Peekbank database contains two major types of data: (1) metadata regarding
 226 experiments, participants, and trials, and (2) time course looking data, detailing where a
 227 child is looking on the screen at a given point in time (Fig. 2).

228 **Metadata.** Metadata can be separated into four parts: (1) participant-level
 229 information (e.g., demographics), (2) experiment-level information (e.g., the type of eye
 230 tracker used to collect the data), (3) session information (e.g. a participant's age for a
 231 specific experimental session), and (4) trial information (e.g., which images or videos were
 232 presented onscreen, and paired with which audio).

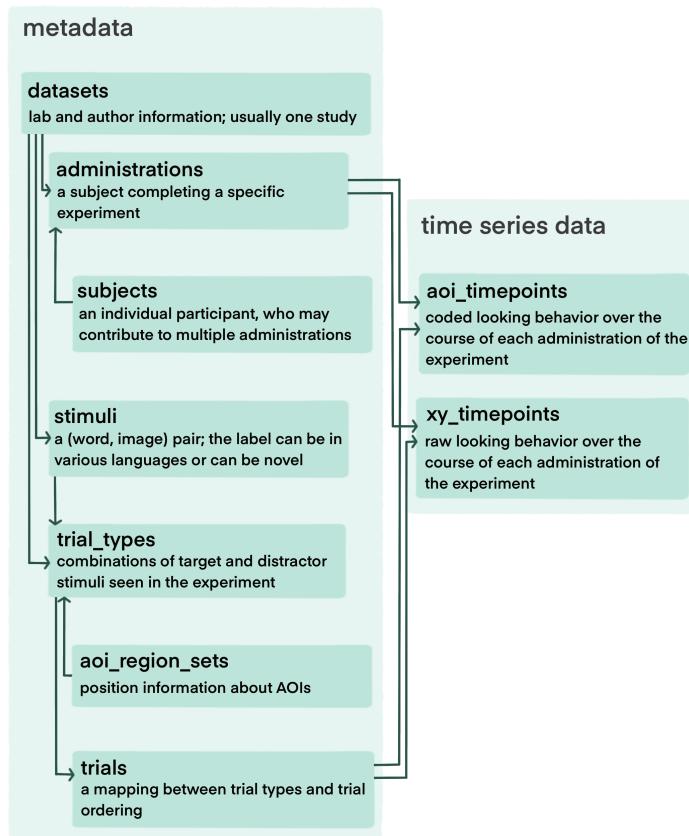


Figure 2. The Peekbank schema. Each darker rectangle represents a table in the relational database.

Participant Information.

All information about individual participants in Peekbank is completely de-identified under United States law, containing none of the key identifiers listed under the “Safe Harbor” standard for data de-identification. All participant-level linkages are made using anonymous participant identifiers.

Invariant information about individuals who participate in one or more studies (e.g., a participant’s first language) is recorded in the `subjects` table, while the `administrations` table contains information about each individual session in a given study (see Session Information, below). This division allows Peekbank to gracefully handle longitudinal designs: a single participant can complete multiple sessions and thus be associated with multiple

243 administrations.

244 Participant-level data includes all participants who have experiment data. In general,
245 we include as many participants as possible in the database and leave it to end-users to
246 apply the appropriate exclusion criteria for their analysis.

247 ***Experiment Information.***

248 The **datasets** table includes information about the lab conducting the study and the
249 relevant publications to cite regarding the data. In most cases, a dataset corresponds to a
250 single study.

251 Information about the experimental design is split across the **trial_types** and
252 **stimuli** tables. The **trial_types** table encodes information about each trial *in the design*
253 *of the experiment*,¹ including the target stimulus and location (left vs. right), the distractor
254 stimulus and location, and the point of disambiguation for that trial. If a dataset used
255 automatic eye-tracking rather than manual coding, each trial type is additionally linked to a
256 set of area of interest (x, y) coordinates, encoded in the **aoi_region_sets** table. The
257 **trial_types** table links trial types to the **aoi_region_sets** table and the **trials** table.
258 Each trial_type record links to two records in the **stimuli** table, identified by the
259 **distractor_id** and the **target_id** fields.

260 Each record in the **stimuli** table is a (word, image) pair. In most experiments, there
261 is a one-to-one mapping between images and labels (e.g., each time an image of a dog
262 appears it is referred to as *dog*). For studies in which there are multiple potential labels per
263 image (e.g., *dog* and *chien* are both used to refer to an image of a dog), images can have
264 multiple rows in the **stimuli** table with unique labels. This structure is useful for studies on

¹ We note that the term *trial* is ambiguous and could be used to refer to both a particular combination of stimuli seen by many participants and a participant seeing that particular combination at a particular point in the experiment. We track the former in the **trial_types** table and the latter in the **trials** table.

265 synonymy or using multiple languages. It is also possible for an image to be associated with
266 a row with no label, if the image appears solely as a distractor (and thus its label is
267 ambiguous). For studies in which the same label refers to multiple images (e.g., the word *dog*
268 refers to an image of a dalmatian and a poodle), the same label can have multiple rows in
269 the `stimuli` table with unique images.

270 ***Session Information.***

271 The `administrations` table includes information about the participant or experiment
272 that may change between sessions of the same study, even for the same participant. This
273 includes the age of the participant, the coding method (eye-tracking vs. hand-coding), and
274 the properties of the monitor that was used. For participant age, we include the fields
275 `lab_age` and `lab_age_units` to record how the original lab encoded age, as well as an
276 additional field, `age`, to encode age in a standardized format across datasets, using months
277 as the common unit of measurement.

278 ***Trial Information.***

279 The `trials` table includes information about a specific participant completing a
280 specific instance of a trial type. This table links each record in the time course looking data
281 (described below) to the trial type and specifies the order of the trials seen by a specific
282 participant.

283 **Time course data.** Raw looking data is a series of looks to areas of interest (AOIs),
284 such as looks to the left or right of the screen, or to (x, y) coordinates on the experiment
285 screen, linked to points in time. For data generated by eye-trackers, we typically have (x, y)
286 coordinates at each time point, which we encode in the `xy_timepoints` table. These looks
287 are also recoded into AOIs according to the AOI coordinates in the `aoi_region_sets` table
288 using the `add_aois()` function in `peekds`, and encoded in the `aoi_timepoints` table. For
289 hand-coded data, we typically have a series of AOIs (i.e., looks to the left vs. right of the

290 screen), but lack information about exact gaze positions on-screen; in these cases the AOIs
291 are recoded into the categories in the Peekbank schema (target, distractor, other, and
292 missing) and encoded in the `aoi_timepoints` table; however, these datasets do not have any
293 corresponding data in the `xy_timepoints` table.

294 Typically, timepoints in the `xy_timepoints` table and `aoi_timepoints` table need to
295 be regularized to center each trial's time around the point of disambiguation – such that 0 is
296 the time of target word onset in the trial (i.e., the beginning of *dog* in *Can you find the*
297 *dog?*). We re-centered timing information to the onset of the target label to facilitate
298 comparison of target label processing across all datasets.² If time values run throughout the
299 experiment rather than resetting to zero at the beginning of each trial, `rezero_times()` is
300 used to reset the time at each trial. After this, each trial's times are centered around the
301 point of disambiguation using `normalize_times()`. When these steps are complete, the
302 time course is ready for resampling.

303 To facilitate time course analysis and visualization across datasets, time course data
304 must be resampled to a uniform sampling rate (i.e., such that every trial in every dataset has
305 observations at the same time points). All data in the database is resampled to 40 Hz
306 (observations every 25 ms), which represents a compromise between retaining fine-grained
307 timing information from datasets with dense sampling rates (maximum sampling rate among
308 current datasets: 500 Hz) while minimizing the possibility of introducing artifacts via
309 resampling for datasets with lower sampling rates (minimum sampling rate for current
310 datasets: 30 Hz). Further, 25 ms is a mathematically convenient interval for ensuring
311 consistent resampling; we found that using 33.333 ms (30 Hz) as our interval simply
312 introduced a large number of technical complexities. The resampling operation is

² While information preceding the onset of the target label in some datasets such as co-articulation cues (Mahr, McMillan, Saffran, Ellis Weismer, & Edwards, 2015) or adjectives (Fernald, Marchman, & Weisleder, 2013) can in principle disambiguate the target referent, we use a standardized point of disambiguation based on the onset of the label for the target referent. Onset times for other potentially disambiguating information (such as adjectives) can typically be recovered from the raw data provided on OSF.

313 accomplished using the `resample_times()` function. During the resampling process, we
314 interpolate using constant interpolation, selecting for each interpolated timepoint the looking
315 location for the earlier-observed time point in the original data for both `aoi_timepoints`
316 and `xy_timepoints` data. Compared to linear interpolation (see e.g., Wass, Smith, &
317 Johnson, 2013) – which fills segments of missing or unobserved time points by interpolating
318 between the observed locations of timepoints at the beginning and end of the interpolated
319 segment –, constant interpolation has the advantage that it is more conservative, in the sense
320 that it does not introduce new look locations beyond those measured in the original data.
321 One possible application of our new dataset is investigating the consequences of other
322 interpolation functions for data analysis.

323 Processing, Validation, and Ingestion

324 Although Peekbank provides a common data format, the crux issue of populating the
325 database is the conversion of existing datasets to this format. Each dataset is imported via a
326 custom import script, which documents the process of conversion. Often various decisions
327 must be made in this import process (for example, how to characterize a particular trial type
328 within the options available in the Peekbank schema); these scripts provide a reproducible
329 record of this decision-making process. Our data import repository (available on GitHub at
330 <https://github.com/langcog/peekbank-data-import>) contains all of these scripts, links to
331 internal documentation on data import, and a set of generic import templates for different
332 formats.

333 Many of the specific operations involved in importing a dataset can be abstracted
334 across datasets. The `peekds` package offers a library of these functions. Once the data have
335 been extracted in a tabular form, the package also offers a validation function that checks
336 whether all tables have the required fields and data types expected by the database. In an
337 effort to double check the data quality and to make sure that no errors are made in the

338 importing script, we also typically perform a visual check of the import process, creating a
339 time course plot to replicate the results in the paper that first presented each dataset. Once
340 this plot has been created and checked for consistency and all tables pass our validation
341 functions, the processed dataset is ready for reprocessing into the database using the
342 `peekbank` library. This library applies additional data checks, and adds the data to the
343 MySQL database using the Django web framework.

344 To date, the import process has been carried out by the Peekbank team using data
345 offered by other research teams. There is no technical obstacle to data contributors also
346 providing an import script to facilitate contribution, though in practice creating these scripts
347 requires familiarity with both R scripting and the specific Peekbank schema; writing a first
348 import script can be somewhat time-consuming. To support future data contributions,
349 import script templates and examples are available for both hand-coded datasets and
350 automatic eye-tracking datasets for research teams to adapt to their data. These import
351 templates walk researchers through each step of data processing using example datasets from
352 Peekbank and include explanations of key decision points, examples of how to use various
353 helper functions available in `peekds`, and further details about the database schema.

354 Current Data Sources

355 The database currently includes 20 looking-while-listening datasets comprising $N=1594$
356 total participants (Table 1). The current data represents a convenience sample of datasets
357 that were (a) datasets collected by or available to Peekbank team members, (b) made
358 available to Peekbank after informal inquiry or (c) datasets that were openly available. Most
359 datasets (14 out of 20 total) consist of data from monolingual native English speakers. They
360 span a wide age spectrum with participants ranging from 9 to 70 months of age, and are
361 balanced in terms of gender (47.30% female; 50.40% male; 2.30% unreported). The datasets
362 vary across a number of design-related dimensions, and include studies using manually coded

Table 1
Overview of the datasets in the current database.

Study Citation	Dataset name	N	Mean age (mos.)	Age range (mos.)	Method	Language
Adams et al., 2018	adams_marchman_2018	69	17.1	13–20	manual coding	English
Byers-Heinlein et al., 2017	byers-heinlein_2017	48	20.1	19–21	eye-tracking	English, French
Casillas et al., 2017	casillas_tseltal_2015	23	31.3	9–48	manual coding	Tseltal
Fernald et al., 2013	fmw_2013	80	20.0	17–26	manual coding	English
Frank et al., 2016	frank_tablet_2016	69	35.5	12–60	eye-tracking	English
Garrison et al., 2020	garrison_bergelson_2020	35	14.5	12–18	eye-tracking	English
Hurtado et al., 2007	xsectional_2007	49	23.8	15–37	manual coding	Spanish
Hurtado et al., 2008	hurtado_2008	76	21.0	17–27	manual coding	Spanish
Mahr et al., 2015	mahr_coartic	29	20.8	18–24	eye-tracking	English
Perry et al., 2017	perry_cowpig	45	20.5	19–22	manual coding	English
Pomper & Saffran, 2016	pomper_saffran_2016	60	44.3	41–47	manual coding	English
Pomper & Saffran, 2019	pomper_salientme	44	40.1	38–43	manual coding	English
Potter & Lew-Williams, unpub.	potter_canine	36	23.8	21–27	manual coding	English
Potter et al., 2019	potter_remix	44	22.6	18–29	manual coding	Spanish, English
Ronfard et al., 2021	ronfard_2021	40	20.0	18–24	manual coding	English
Swingley & Aslin, 2002	swingley_aslin_2002	50	15.1	14–16	manual coding	English
Weisleder & Fernald, 2013	weisleder_stl	29	21.6	18–27	manual coding	Spanish
Yurovsky & Frank, 2017	attword_processed	288	25.5	13–59	eye-tracking	English
Yurovsky et al., 2013	reflook_socword	435	33.6	12–70	eye-tracking	English
Yurovsky et al., unpub.	reflook_v4	45	34.2	11–60	eye-tracking	English

363 video recordings and automated eye-tracking methods (e.g., Tobii, EyeLink) to measure gaze
 364 behavior. All studies tested familiar items, but the database also includes 5 datasets that
 365 tested novel pseudo-words in addition to familiar words. Users interested in a subset of the
 366 data (e.g., only trials testing familiar words) can filter out unwanted trials using columns
 367 available in the schema (e.g., using the column `stimulus_novelty` in the `stimuli` table).

368 Versioning and Reproducibility

369 The content of Peekbank will change as we add additional datasets and revise previous
 370 ones. To facilitate reproducibility of analyses, we use a versioning system by which
 371 successive releases are assigned a name reflecting the year and version, e.g., 2022.1. By
 372 default, users will interact with the most recent version of the database available, though the
 373 `peekbankr` API allows researchers to run analyses against any previous version of the
 374 database. For users with intensive use-cases, each version of the database may be
 375 downloaded as a compressed .sql file and installed on a local MySQL server.

376 Peekbank allows for fully reproducible analyses using our source data, but the goal is

377 not to reproduce precisely the analyses – or even the datasets – in the publications whose
378 data we archive. Because of our emphasis on a standardized data importing and formatting
379 pipeline, there may be minor discrepancies in the time course data that we archive compared
380 with those reported in original publications. Further, we archive all of the data that are
381 provided to us – including participants that might have been excluded in the original studies,
382 if these data are available – rather than attempting to reproduce specific exclusion criteria.
383 We hope that Peekbank can be used as a basis for comparing different exclusion and filtering
384 criteria – as such, an inclusive policy regarding importing all available data helps us provide
385 a broad base of data for investigating these decisions.

386 **Interfacing with Peekbank**

387 **Peekbankr**

388 The `peekbankr` API offers a way for users to access data from the database and
389 flexibly analyze it in R. The majority of API calls simply allow users to download tables (or
390 subsets of tables) from the database. In particular, the package offers the following functions:

- 391 • `connect_to_peekbank()` opens a connection with the Peekbank database to allow
392 tables to be downloaded with the following functions
- 393 • `get_datasets()` gives each dataset name and its citation information
- 394 • `get_subjects()` gives information about persistent participant identifiers (e.g., native
395 languages, sex)
- 396 • `get_administrations()` gives information about specific experimental
397 administrations (e.g., participant age, monitor size, gaze coding method)
- 398 • `get_stimuli()` gives information about word–image pairings that appeared in
399 experiments
- 400 • `get_trial_types()` gives information about pairings of stimuli that appeared in the

401 experiment (e.g., point of disambiguation, target and distractor stimuli, condition,
402 language)

- 403 • `get_trials()` gives the trial orderings for each administration, linking trial types to
404 the trial IDs used in time course data
- 405 • `get_aoi_region_sets()` gives coordinate regions for each area of interest (AOI)
406 linked to trial type IDs
- 407 • `get_xy_timepoints()` gives time course data for each participant's looking behavior
408 in each trial, as (x, y) coordinates on the experiment monitor
- 409 • `get_aoi_timepoints()` gives time course data for each participant's looking behavior
410 in each trial, coded into areas of interest

411 Once users have downloaded tables, they can be merged using `join` commands via their
412 linked IDs. A set of standard merges are shown below in the “Peekbank in Action” section;
413 these allow the common use-case of examining time course data and metadata jointly.

414 Because of the size of the XY and AOI data tables, downloading data across multiple
415 studies can be time-consuming. Many of the most common analyses of the Peekbank data
416 require downloading the `aoi_timepoints` table, thus we have put substantial work into
417 optimizing transfer times. In particular, `connect_to_peekbank` offers a data compression
418 option, and `get_aoi_timepoints` by default downloads time courses via a compressed
419 (run-length encoded) representation, which is then uncompressed on the client side. More
420 information about these options (including how to modify them) can be found in the
421 package documentation.

422 Shiny App

423 One goal of the Peekbank project is to allow a wide range of users to easily explore and
424 learn from the database. We therefore have created an interactive web application –

425 peekbank-shiny – that allows users to quickly and easily create informative visualizations
426 of individual datasets and aggregated data (<https://peekbank-shiny.com/>).
427 peekbank-shiny is built using Shiny, a software package for creating web apps for data
428 exploration with R, as well as the peekbankr package. All code for the Shiny app is publicly
429 available (<https://github.com/langcog/peekbank-shiny>). The Shiny app allows users to
430 create commonly used visualizations of looking-while-listening data, based on data from the
431 Peekbank database. Specifically, users can visualize:

- 432 1. the *time course of looking data* in a profile plot depicting infant target looking across
433 trial time
- 434 2. *overall accuracy*, defined as the proportion target looking within a specified analysis
435 window
- 436 3. *reaction times* in response to a target label, defined as how quickly participants shift
437 fixation to the target image on trials in which they were fixating on the distractor
438 image at onset of the target label
- 439 4. an *onset-contingent plot*, which shows the time course of participant looking as a
440 function of their look location at the onset of the target label

441 Users are given various customization options for each of these visualizations, e.g.,
442 choosing which datasets to include in the plots, controlling the age range of participants,
443 splitting the visualizations by age bins, and controlling the analysis window for time course
444 analyses. Plots are then updated in real time to reflect users' customization choices. A
445 screenshot of the app is shown in Figure 3. The Shiny app thus allows users to quickly
446 inspect basic properties of Peekbanks datasets and create reproducible visualizations without
447 incurring any of the technical overhead required to access the database through R.

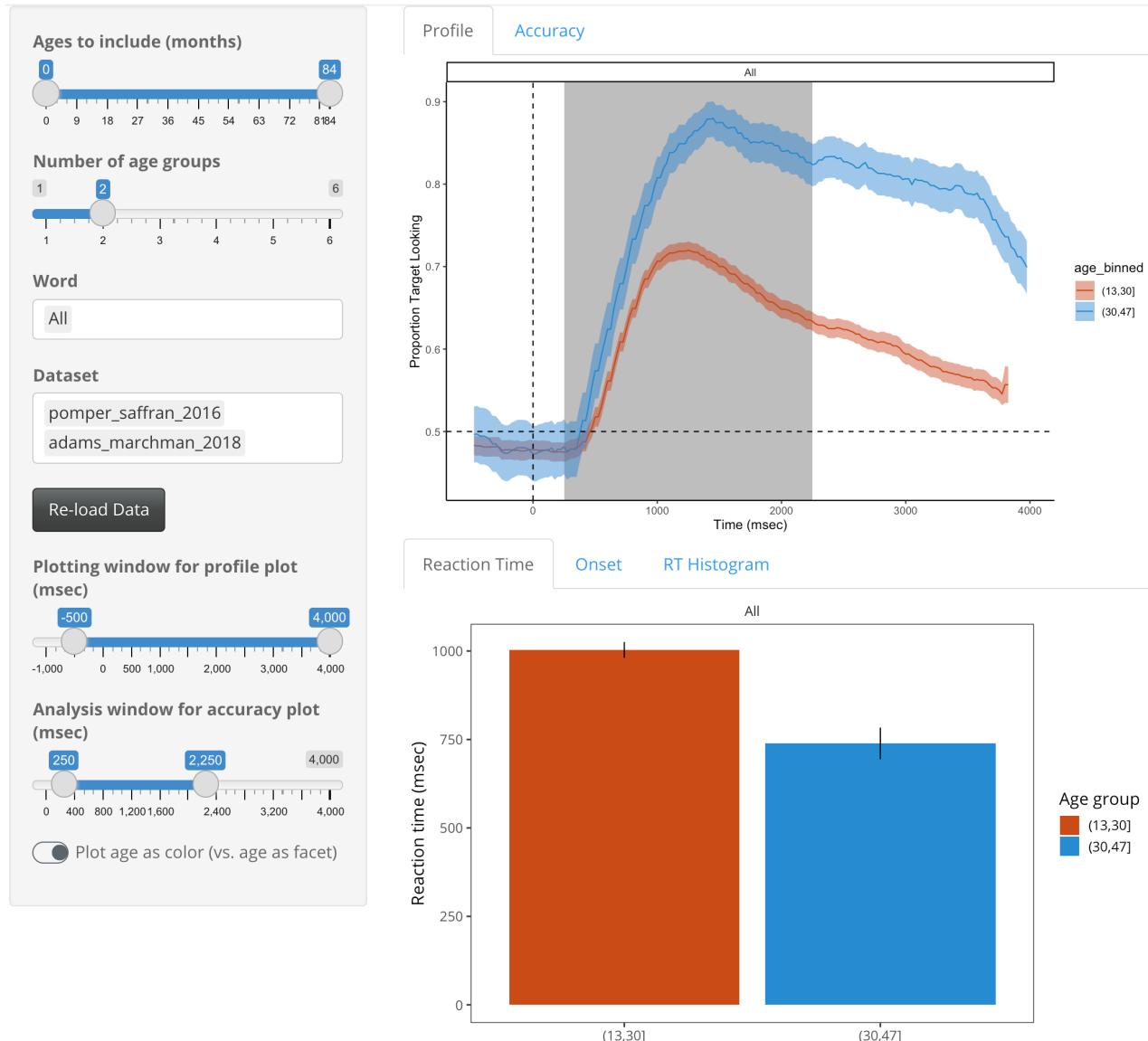


Figure 3. Screenshot of the Peekbank Shiny app, which shows a variety of standard analysis plots as a function of user-selected datasets, words, age ranges, and analysis windows. Shown here are mean reaction time and proportion target looking over time by age group for two selected datasets.

448 OSF site

449 In addition to the Peekbank database proper, all data is openly available on the
450 Peekbank OSF webpage (<https://osf.io/pr6wu/>). The OSF site also includes the original raw
451 data (both time series data and metadata, such as trial lists and participant logs) that was
452 obtained for each study and subsequently processed into the standardized Peekbank format.
453 Where available, the OSF page also includes additional information about the stimuli used in
454 each dataset, including in some instances the original stimulus sets (e.g., image and audio
455 files).

456 **Peekbank in Action**

457 In the following section, we provide examples of how users can access and analyze the
458 data in Peekbank. First, we provide an overview of some general properties of the datasets
459 in the database. We then demonstrate two potential use-cases for Peekbank data. In each
460 case, we provide sample code to demonstrate the ease of doing simple analyses using the
461 database. Our first example shows how we can investigate the findings of a classic study.
462 This type of investigation can be a very useful exercise for teaching students about best
463 practices for data analysis (e.g., Hardwicke et al., 2018) and also provides an easy way to
464 explore looking-while-listening time course data in a standardized format. Our second
465 example shows an exploration of developmental changes in the recognition of particular
466 words. Besides its theoretical interest (which we will explore more fully in subsequent work),
467 this type of analysis could in principle be used for optimizing the stimuli for new
468 experiments, especially as the Peekbank dataset grows and gains coverage over a greater
469 number of items. All analyses are conducted using R [Version 4.1.1; R Core Team (2021)]³

³ We, furthermore, used the R-packages *dplyr* [Version 1.0.7; Wickham, François, Henry, and Müller (2021)], *forcats* [Version 0.5.1; Wickham (2021a)], *ggplot2* [Version 3.3.5; Wickham (2016)], *ggthemes* [Version 4.2.4; Arnold (2021)], *here* [Version 1.0.1; Müller (2020)], *papaja* [Version 0.1.0.9997; Aust and Barth (2020)], *peekbankr* [Version 0.1.1.9002; Braginsky, MacDonald, and Frank (2021)], *purrr* [Version 0.3.4; Henry and

470 **General Descriptives**

Study Citation	Unique Items	Prop. Target	95% CI
Adams et al., 2018	8	0.65	[0.63, 0.67]
Byers-Heinlein et al., 2017	6	0.55	[0.52, 0.58]
Casillas et al., 2017	30	0.59	[0.54, 0.63]
Fernald et al., 2013	12	0.65	[0.63, 0.67]
Frank et al., 2016	24	0.64	[0.6, 0.68]
Garrison et al., 2020	87	0.60	[0.56, 0.64]
Hurtado et al., 2007	8	0.59	[0.55, 0.63]
Hurtado et al., 2008	12	0.61	[0.59, 0.63]
Mahr et al., 2015	10	0.71	[0.68, 0.74]
Perry et al., 2017	12	0.61	[0.58, 0.63]
Pomper & Saffran, 2016	40	0.77	[0.75, 0.8]
Pomper & Saffran, 2019	16	0.74	[0.72, 0.75]
Potter & Lew-Williams, unpub.	16	0.65	[0.61, 0.68]
Potter et al., 2019	8	0.63	[0.58, 0.67]
Ronfard et al., 2021	8	0.69	[0.65, 0.73]
Swingley & Aslin, 2002	22	0.57	[0.55, 0.59]
Weisleder & Fernald, 2013	12	0.63	[0.6, 0.66]
Yurovsky & Frank, 2017	6	0.63	[0.62, 0.65]
Yurovsky et al., 2013	6	0.61	[0.6, 0.63]
Yurovsky et al., unpub.	10	0.61	[0.57, 0.65]

Table 2

Average proportion target looking in each dataset.

471 One of the values of the uniform data format we use in Peekbank is the ease of
 472 providing cross-dataset descriptions that can give an overview of some of the general
 473 patterns found in our data. A first broad question is about the degree of accuracy in word
 474 recognition found across studies. In general, participants demonstrated robust, above-chance
 475 word recognition in each dataset (chance=0.5). Table 2 shows the average proportion of
 476 target looking within a standard critical window of 367-2000ms after the onset of the label
 477 for each dataset (Swingley & Aslin, 2002). Proportion target looking was generally higher for
 478 familiar words ($M = 0.66$, 95% CI = [0.65, 0.67], $n = 1543$) than for novel words learned
 479 during the experiment ($M = 0.59$, 95% CI = [0.58, 0.61], $n = 822$).

480 A second question of interest is about the variability across items (i.e., target labels)

Wickham (2020)], *readr* [Version 2.0.1; Wickham and Hester (2021)], *stringr* [Version 1.4.0; Wickham (2019)], *tibble* [Version 3.1.4; Müller and Wickham (2021)], *tidyR* [Version 1.1.3; Wickham (2021b)], *tidyverse* [Version 1.3.1; Wickham et al. (2019)], *tinylabels* (Barth, 2021), *viridis* [Version 0.6.1; Garnier et al. (2021a); Garnier et al. (2021b)], *viridisLite* [Version 0.4.0; Garnier et al. (2021b)], and *xtable* [Version 1.8.4; Dahl, Scott, Roosen, Magnusson, and Swinton (2019)].

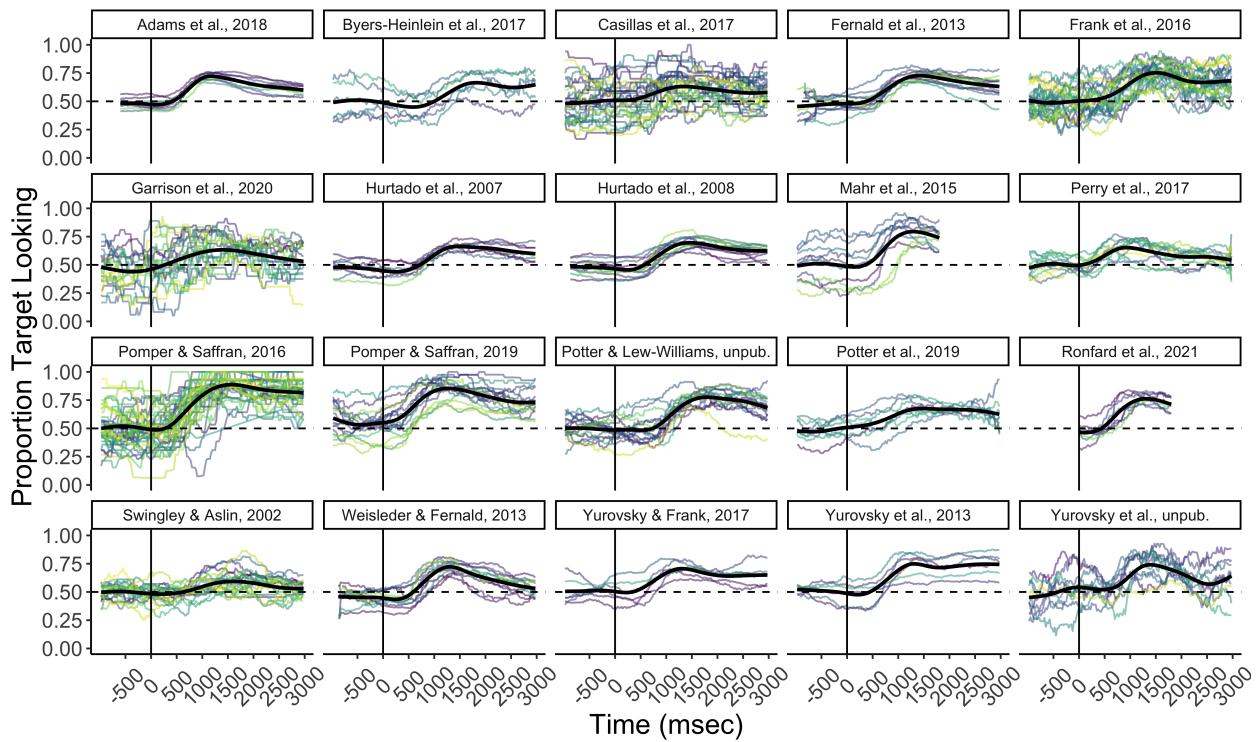


Figure 4. Item-level variability in proportion target looking within each dataset (chance=0.5). Time is centered on the onset of the target label (vertical line). Colored lines represent specific target labels. Black lines represent smoothed average fits based on a general additive model using cubic splines.

481 within specific studies. Some studies use a smaller set of items (e.g., 8 nouns, Adams et al.,
 482 2018) while others use dozens of different items (e.g., Garrison, Baudet, Breitfeld, Aberman,
 483 & Bergelson, 2020). Figure 4 gives an overview of the variability in proportion looking to the
 484 target item for individual words in each dataset. Although all datasets show a gradual rise in
 485 average proportion target looking over chance performance, the number of unique target
 486 labels and their associated accuracy vary widely across datasets.

487 **Investigating prior findings: Swingley and Aslin (2002)**

488 Swingley and Aslin (2002) investigated the specificity of 14-16-month-olds' word
 489 representations using the looking-while-listening paradigm, asking whether recognition would
 490 be slower and less accurate for mispronunciations, e.g. *opal* (mispronunciation) instead of

491 *apple* (correct pronunciation).⁴ In this short vignette, we show how easily the data in
 492 Peekbank can be used to visualize this result. Our goal here is not to provide a precise
 493 analytical reproduction of the analyses reported in the original paper, but rather to
 494 demonstrate the use of the Peekbank framework to analyze datasets of this type. In
 495 particular, because Peekbank uses a uniform data import standard, it is likely that there will
 496 be minor numerical discrepancies between analyses on Peekbank data and analyses that use
 497 another processing pipeline.

```
library(peekbankr)
aoi_timepoints <- get_aoi_timepoints(dataset_name = "swingley_aslin_2002")
administrations <- get_administrations(dataset_name = "swingley_aslin_2002")
trial_types <- get_trial_types(dataset_name = "swingley_aslin_2002")
trials <- get_trials(dataset_name = "swingley_aslin_2002")
```

498 We begin by retrieving the relevant tables from the database, `aoi_timepoints`,
 499 `administrations`, `trial_types`, and `trials`. As discussed above, each of these can be
 500 downloaded using a simple API call through `peekbankr`, which returns dataframes that
 501 include ID fields. These ID fields allow for easy joining of the data into a single dataframe
 502 containing all of the information necessary for the analysis.

```
swingley_data <- aoi_timepoints |>
  left_join(administrations) |>
  left_join(trials) |>
  left_join(trial_types) |>
  filter(condition != "filler") |>
  mutate(condition = if_else(condition == "cp", "Correct", "Mispronounced"))
```

503 As the code above shows, once the data are joined, condition information for each
 504 timepoint is present and so we can easily filter out filler trials and set up the conditions for
 505 further analysis.

⁴ The original paper investigated both close (e.g., *opple*, /apl/) and distant (e.g., *opal*, /opl/) mispronunciations. For simplicity, here we combine both mispronunciation conditions since the close vs. distant mispronunciation manipulation showed no effect in the original paper.

```

accuracies <- swingley_data |>
  group_by(condition, t_norm, administration_id) |>
  summarize(correct = sum(aoi == "target") /
    sum(aoi %in% c("target", "distractor"))) |>
  group_by(condition, t_norm) |>
  summarize(mean_correct = mean(correct),
    ci = 1.96 * sd(correct) / sqrt(n()))

```

506 The final step in our analysis is to create a summary dataframe using `dplyr`
 507 commands. We first group the data by timestep, participant, and condition and compute the
 508 proportion looking at the correct image. We then summarize again, averaging across
 509 participants, computing both means and 95% confidence intervals (via the approximation of
 510 1.96 times the standard error of the mean). The resulting dataframe can be used for
 511 visualization of the time course of looking.

512 Figure 5 shows the average time course of looking for the two conditions, as produced
 513 by the code above. Looks after the correctly pronounced noun appeared both faster
 514 (deviating from chance earlier) and more accurate (showing a higher asymptote). Overall,
 515 this example demonstrates the ability to produce this visualization in just a few lines of code.

516 Item analyses

517 A second use-case for Peekbank is to examine item-level variation in word recognition.
 518 Individual datasets rarely have enough statistical power to show reliable developmental
 519 differences within items. To illustrate the power of aggregating data across multiple datasets,
 520 we select the four words with the most data available across studies and ages (apple, book,
 521 dog, and frog) and show average recognition trajectories.

522 Our first step is to collect and join the data from the relevant tables including
 523 timepoint data, trial and stimulus data, and administration data (for participant ages). We
 524 join these into a single dataframe for easy manipulation; this dataframe is a common

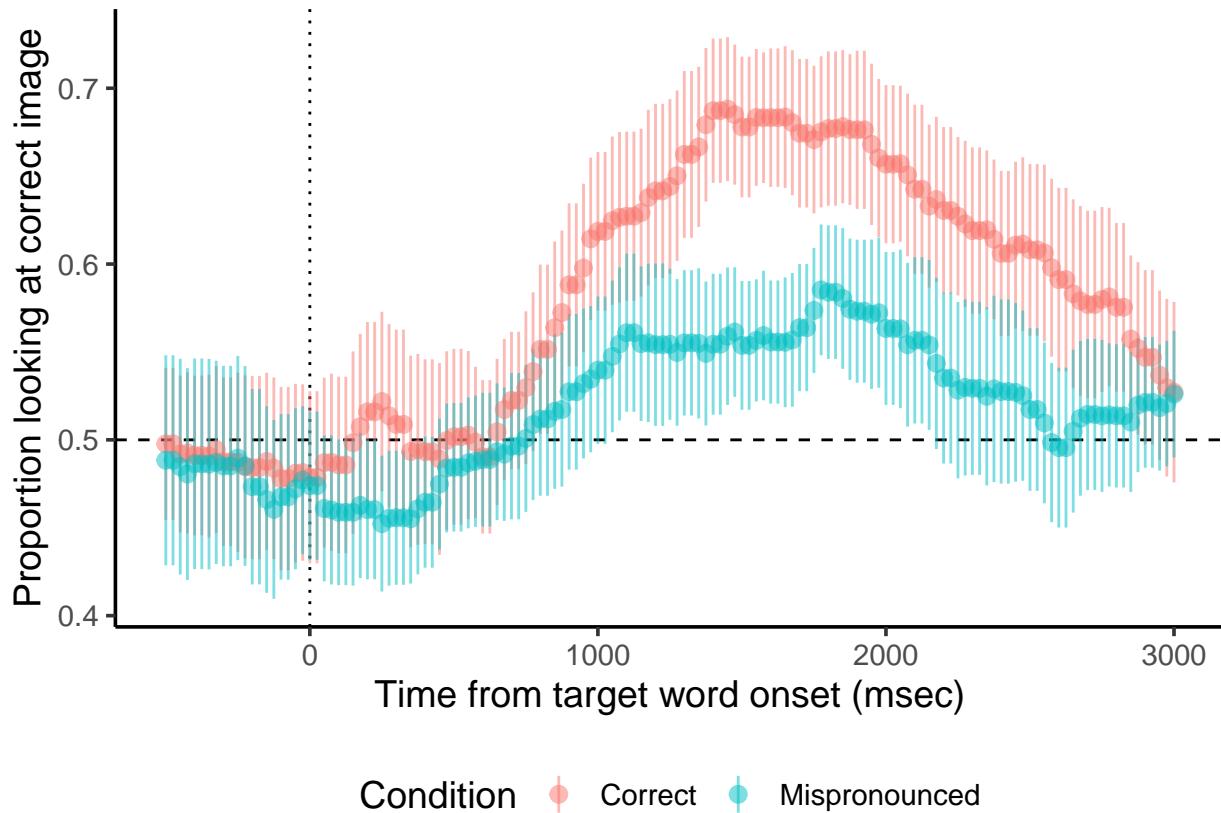


Figure 5. Proportion looking at the correct referent by time from the point of disambiguation (the onset of the target noun) in Swingley & Aslin (2002). Colors show the two pronunciation conditions; points give means and ranges show 95% confidence intervals. The dotted line shows the point of disambiguation and the dashed line shows chance performance.

525 starting point for analyses of item-level data.

```
all_aoi_timepoints <- get_aoi_timepoints()
all_stimuli <- get_stimuli()
all_administrations <- get_administrations()
all_trial_types <- get_trial_types()
all_trials <- get_trials()

aoi_data_joined <- all_aoi_timepoints |>
  right_join(all_administrations) |>
  right_join(all_trials) |>
```

```

right_join(all_trial_types) |>
  mutate(stimulus_id = target_id) |>
  right_join(all_stimuli) |>
  select(administration_id, english_stimulus_label, age, t_norm, aoi)

```

526 Next we select a set of four target words (chosen based on having more than 100
 527 children contributing data for each word across several one-year age groups). We create age
 528 groups, aggregate, and compute timepoint-by-timepoint confidence intervals using the z
 529 approximation.

```

target_words <- c("book", "dog", "frog", "apple")

target_word_data <- aoi_data_joined |>
  filter(english_stimulus_label %in% target_words) |>
  mutate(age_group = cut(age, breaks = seq(12, 48, 12))) |>
  filter(!is.na(age_group)) |>
  group_by(t_norm, administration_id, age_group, english_stimulus_label) |>
  summarise(correct = sum(aoi == "target") /
    sum(aoi %in% c("target", "distractor"))) |>
  group_by(t_norm, age_group, english_stimulus_label) |>
  summarise(ci = 1.96 * sd(correct, na.rm=TRUE) / sqrt(length(correct)),
            correct = mean(correct, na.rm=TRUE),
            n = n())

```

530 Finally, we plot the data as time courses split by age. Our plotting code is shown below
 531 (with styling commands removed for clarity). Figure 6 shows the resulting plot, with time
 532 courses for each of three (rather coarse) age bins. Although some baseline effects are visible
 533 across items, we still see clear and consistent increases in looking to the target, with the

534 increase appearing earlier and in many cases asymptoting at a higher level for older children.

```
ggplot(target_word_data,
       aes(x = t_norm, y = correct, col = age_group)) +
  geom_line() +
  geom_linerange(aes(ymin = correct - ci, ymax = correct + ci),
                 alpha = .2) +
  facet_wrap(~english_stimulus_label)
```

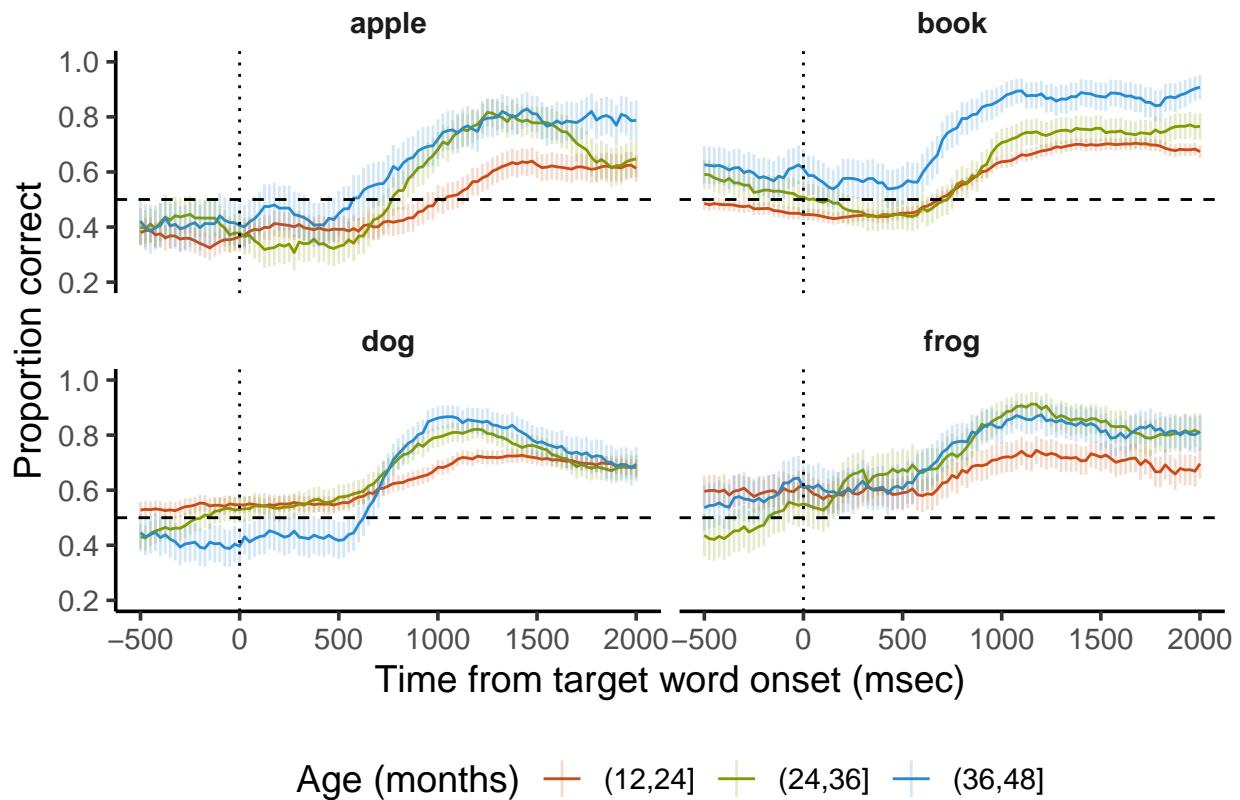


Figure 6. Time course plot for four well-represented target items in the Peekbank dataset, split by three age groups. Each line represents children's average looking to the target image after the onset of the target label (dashed vertical line). Error bars represent 95% CIs.

535 This simple averaging approach is a proof-of-concept to demonstrate some of the
 536 potential of the Peekbank dataset. An eye-movement trajectory on an individual trial reflects
 537 myriad factors, including the age and ability of the child, the target and distractor stimuli on
 538 that trial, the position of the trial within the experiment, and the general parameters of the

539 experiment (for example, stimulus timing, eye-tracker type and calibration, etc.). Although
540 we often neglect these statistically in the analysis of individual experiments – for example,
541 averaging across items and trial orders – they may lead to imprecision when we average
542 across multiple studies in Peekbank. For example, studies with older children may use more
543 difficult items or faster trial timing, leading to the impression that children’s abilities overall
544 increase more slowly than they do in fact. Even in our example in Figure 6, we see hints of
545 this confounding – for example, the low baseline looks to *apple* may be an artifact of an
546 attractive distractor being paired with this item in one or two studies. In future work, we
547 hope to introduce model-based analytic methods that use mixed effects regression to factor
548 out study-level and individual-level variance in order to recover developmental effects more
549 appropriately (see e.g., Zettersten et al., 2021 for a prototype of such an analysis).

550

Discussion

551 Theoretical progress in understanding child development requires rich datasets, but
552 collecting child data is expensive, difficult, and time-intensive. Recent years have seen a
553 growing effort to build open source tools and pool research efforts to meet the challenge of
554 building a cumulative developmental science (Bergmann et al., 2018; Frank, Braginsky,
555 Yurovsky, & Marchman, 2017; Sanchez et al., 2019; The ManyBabies Consortium, 2020).
556 The Peekbank project expands on these efforts by building an infrastructure for aggregating
557 eye-tracking data across studies, with a specific focus on the looking-while-listening
558 paradigm. This paper presents an overview of the structure of the database, shows how users
559 can access the database, and demonstrates how it can be used both to investigate prior
560 experiments and to synthesize data across studies.

561 The current database has a number of limitations, particularly in the number and
562 diversity of datasets it contains. With 20 datasets currently available in the database,
563 idiosyncrasies of particular designs and condition manipulations still have a substantial

564 influence on the results of particular analyses, as discussed above in our item analysis
565 example. Expanding the set of distinct datasets will allow us to increase the number of
566 datasets that contain specific items, leading to more robust generalizations across the many
567 sources of variation that are confounded within studies (e.g., item set, participant age range,
568 and specific experimental parameters). A critical next step will be the development of
569 analytic models that take this structure into account in making generalizations across
570 datasets.

571 A second limitation stems from the fact that the database represents a convenience
572 sample of data readily available to the Peekbank team, which leads the database to be
573 relatively homogeneous in a number of key respects. First, the datasets primarily come from
574 labs that share similar theoretical perspectives and implement the looking-while-listening
575 method in similar ways. The current database is also limited by the relatively homogeneous
576 background of its participants, both with respect to language (almost entirely monolingual
577 native English speakers) and cultural background (Henrich, Heine, & Norenzayan, 2010;
578 Muthukrishna et al., 2020). Increasing the diversity of lab sources, participant backgrounds,
579 and languages will expand the scope of the generalizations we can form about child word
580 recognition, while also providing new opportunities for describing cross-lab, cross-cultural,
581 and cross-linguistic variation.

582 Towards the goal of expanding our database, we invite researchers to contribute their
583 data. On the Peekbank website, we provide technical documentation for potential
584 contributors. Although we anticipate being involved in most new data imports, as discussed
585 above, our import process is transparently documented and the repository contains examples
586 for most commonly-used eye-trackers. Contributing data to an open repository also can raise
587 questions about participant privacy. Potential contributors should consult with their local
588 institutional review boards for guidance on any challenges, but we do not foresee obstacles
589 because of the de-identified nature of the data. Under United States regulation, all data

590 contributed to Peekbank are considered de-identified and hence not considered “human
591 subjects data”; hence, institutional review boards should not regulate this contribution
592 process. Under the European Union’s Generalized Data Protection Regulation (GDPR), labs
593 may need to take special care to provide a separate set of participant identifiers that can
594 never be re-linked to their own internal records.

595 While the current database is focused on studies of word recognition, the tools and
596 infrastructure developed in the project can in principle be used to accommodate any
597 eye-tracking paradigm, opening up new avenues for insights into cognitive development.
598 Gaze behavior has been at the core of many key advances in our understanding of infant
599 cognition (Aslin, 2007; Baillargeon, Spelke, & Wasserman, 1985; Bergelson & Swingley, 2012;
600 Fantz, 1963; Liu, Ullman, Tenenbaum, & Spelke, 2017; Quinn, Eimas, & Rosenkrantz, 1993).
601 Aggregating large datasets of infant looking behavior in a single, openly-accessible format
602 promises to bring a fuller picture of infant cognitive development into view.

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