

# Peekbank: Exploring child lexical processing through a large-scale open-source database of developmental eyetracking datasets

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## Abstract

Developing lexical processing skills - the ability to rapidly process words and link them to referents in context - is central to children's early language development. Children's lexical processing is typically studied in the looking-while-listening paradigm, which measures infants' fixation of a target object (as opposed to a distracter) after hearing a target label. In the following paper, we present a large-scale open-source database of infant and toddler looking-while-listening studies. The goal of this database is to address theoretical and methodological challenges in measuring infant vocabulary development that go beyond the scope of individual studies. We present three preliminary analyses from the current database: (1) models capturing item-level variability in infants' lexical processing across age; (2) an analysis of how a central methodological decision - selecting the time window of analysis - impacts modeling results; (3) an analysis demonstrating the link between the age of acquisition of specific words and children's ability to rapidly and accurately link those words to their referents. Future efforts will expand the scope of the current database to advance our understanding of participant-level and item-level variation in children's vocabulary development.

**Keywords:** lexical processing; eyetracking; database; vocabulary development; looking-while-listening

## Introduction

Across their first years of life, children learn words in their native tongues at a rapid pace (Braginsky, Yurovsky, Marchman, & Frank, 2019). A key part of the word learning process is children's ability to rapidly process words and link them to relevant meanings in context - often referred to as lexical processing. Developing lexical processing skills builds a foundation for children's language development and is predictive of both linguistic and more general cognitive outcomes later in life (Bleses, Makrinsky, Dale, Højen, & Ari, 2016; Marchman et al., 2018).

Lexical processing is traditionally studied in "looking-while-listening" studies (alternatively referred to as the intermodal preferential looking procedure) (Fernald, Zangl, Portillo, & Marchman, 2008; Hirsh-Pasek, Cauley, Golinkoff, & Gordon, 1987). In such studies, infants listen to a sentence prompting a specific referent (e.g., Look at the dog!) while viewing two images on the screen (e.g., an image of a dog - the target image - and an image of a duck - the distractor image). Infants' lexical processing is measured in terms of how quickly and accurately infants subsequently fixate the correct target image after hearing its label. Studies using this basic design have contributed to our understanding of a wide range

of questions in language development (Golinkoff, Ma, Song, & Hirsh-Pasek, 2013), including infants' early noun knowledge (Bergelson & Swingle, 2012), phonological representations of words (Swingle & Aslin, 2000), prediction during language processing (Lew-Williams & Fernald, 2007), and individual differences in language development (Marchman et al., 2018).

While the looking-while-listening paradigm has been highly fruitful in advancing understanding of early word knowledge, fundamental questions remain both about the nature of children's early word knowledge and the nature of the method itself. One central question relates to understanding word-specific variability across development, and generalizing lexical processing on the level of specific words. Most studies of infant lexical processing focus on generalizing performance across participants, and are constrained in their ability to provide generalizations across the item level - the level of specific words. Generalizing behavior on the level of both participants and items simultaneously is often difficult in the context of a solitary study, especially given practical constraints on the number of trials (and consequently items) tested within a given infant. However, drawing inferences about item-level variability is key to many questions in how word learning unfolds, including how properties of the language input influence lexical development (Goodman, Dale, & Li, 2008; Roy, Frank, Decamp, Miller, & Roy, 2015). One key to meeting this challenge is having sufficiently large datasets to interrogate variability in lexical processing on the item level.

A second question relates to evaluating methodological best-practices. In particular, many fundamental analytic decisions vary substantially across studies. For example, researchers vary in their decisions regarding how to select time windows for analysis, modeling how lexical processing unfolds over time, and the appropriate transformations to perform on the dependent measure of target fixations (Csibra, Hernik, Mascaró, Tatone, & Lengyel, 2016; Fernald et al., 2008; Huang & Snedeker, 2020). Establishing best practices regarding analytic decisions of this kind requires a large database of infant lexical processing studies, in order to independently test the potential consequences of a variety of methodological decisions on the interpretation of study results.

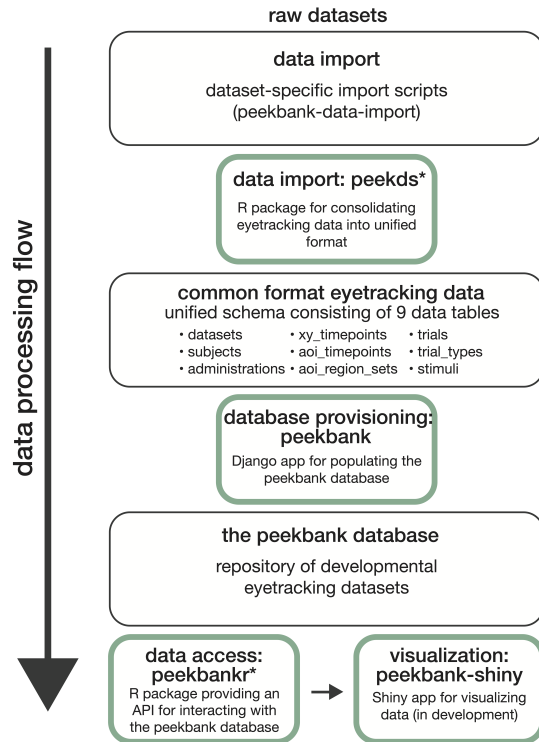


Figure 1: Overview of the peekbank data ecosystem.

## Peekbank: A large-scale database of looking-while-listening-studies

What these questions and challenges share is that they are difficult to answer at the scale of a single looking-while-listening study. In order to address these questions, we introduce peekbank, a flexible and reproducible interface to an open database of developmental eye-tracking studies. Here, we give a brief overview over the key components of the peekbank project and some initial demonstrations of its utility in advancing theoretical and methodological questions in the study of children’s lexical processing. The peekbank project (a) collects a large set of eye-tracking datasets on children’s lexical processing, (b) introduces a data format and processing tools for standardizing eyetracking data across different data sources, and (c) provides an API for quickly accessing and analyzing the database.

## Methods

### Database Framework

The Peekbank data framework consists of three libraries that help to populate and query a relational database (Fig. 1). The `peekds` library (for the R language) helps researchers convert and validate existing datasets to use the relational format used by the database. The `peekbank` library (Python) creates a database with the relational schema and populates it with the standardized datasets produced by `peekds`. The database is implemented in MySQL, an industry standard relational

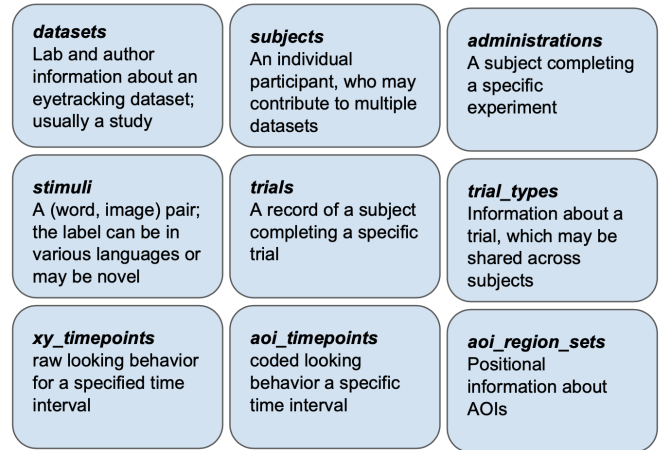


Figure 2: Data schema for the peekbank database.

database, which may be accessed by a variety of programming languages over the internet. The `peekbankr` library (R) provides an application programming interface, or API, that provides high-level abstractions to help researchers run common analysis tasks on the database.

## Data Format and Processing

One of the main challenges in compiling a large-scale eye-tracking dataset is the lack of a shared re-usable data format among labs conducting individual experiments. Different eyetracking methods have different conventions for exporting and structuring data, rendering integrating datasets originating from different labs and data sources difficult to integrate. We developed a common, tidy format for the eye-tracking data in peekbank to ease the process of conducting cross-dataset analyses. The schema of the database (Fig. 2) is sufficiently general to handle heterogeneous datasets from many studies from many labs, including both manually coded and automated eyetracking data.

During data import, raw eyetracking datasets are processed to conform to the peekbank data schema. The centerpiece of the schema is the `aoi_timepoints` table (Fig. 2), which records whether participants looked to the target or distracter stimulus at each timepoint of a given trial. In addition to unifying the data format, we conduct several additional pre-processing steps to facilitate analyses across datasets, including resampling observations to a common sampling rate (40 Hz) and normalizing time relative to the onset of the target label.

## Current Data Sources

| Dataset Name    | N   | Mean Age | Method        |
|-----------------|-----|----------|---------------|
| canine          | 36  | 23.8     | manual coding |
| coartic         | 29  | 20.8     | eyetracking   |
| cowpig          | 45  | 20.5     | manual coding |
| ft_pt           | 69  | 17.1     | manual coding |
| reflook_socword | 435 | 33.6     | eyetracking   |
| reflook_v4      | 347 | 37.2     | eyetracking   |
| salientme       | 44  | 40.1     | manual coding |
| switchingCues   | 60  | 44.3     | manual coding |
| tablet          | 110 | 33.8     | eyetracking   |
| tseltal         | 23  | 31.3     | manual coding |
| yoursmy         | 35  | 14.5     | eyetracking   |

Table 1: Overview over the datasets in the current database.

The database currently includes 11 datasets comprising N=1233 total participants, with 23 to 435 participants per dataset (Table 1). The vast majority of datasets consist of monolingual native English speakers, with the exception of XX. The datasets span a wide age spectrum with participants ranging from 8 to 84 months of age, and are balanced in terms of gender (48% female). The studies in the current database vary across a number of dimensions related to design and methodology. The database includes studies using both manually coded video recordings or automated eyetracking methods to measure children’s gaze behavior. Most studies focused on testing familiar items, but the database also includes studies in which both familiar words and novel pseudowords were tested.

## Results

### General descriptives

(Fig. 3)

### Predicting Age-Related Changes While Generalizing Across Items

Following the approach of Mirman (2014), we used growth curve modeling to assess the timecourse of children’s fixations to the target object at different ages, generalizing across items. Specifically, we predicted children’s proportion of target looking during the critical window from the interaction between age and four orthogonal polynomial time terms (linear, quadratic, cubic, and quartic). We included by-item and by-dataset random effects. Figure 4 depicts the model fit at four different age bins (though not that age was analyzed continuously in the model).

We found that XXXXX.

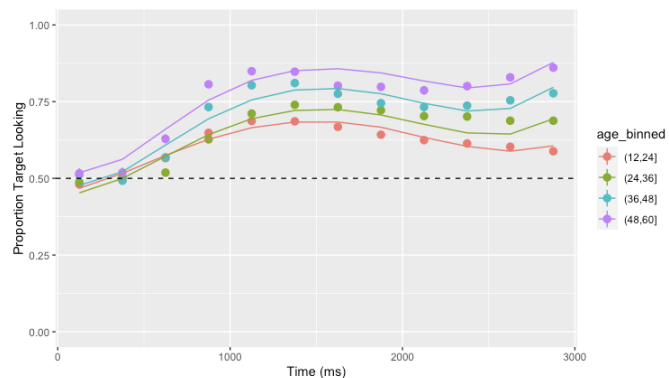


Figure 4: Growth curve models of proportion target looking during the critical target window at each age range (in months).

### Predicting Target Fixation from Word AOA

In the next analysis, we asked whether properties of a specific item - in particular, the age of acquisition (AOA) for a particular item - predict children’s lexical processing. Using estimates of the age of acquisition derived from Wordbank (Frank, Braginsky, Yurovsky, & Marchman, 2017) for the target and the distractor word, we modeled whether earlier-acquired target words are more likely to be fixated accurately. XX.

### Time Window Selection

Following the approach of Peelle and Van Engen (2020), we conducted a multiverse-style analysis considering possible time windows for estimating the effect of age on proportion target looking in linear mixed-effects models. In this analysis, we fit the same model across a wide range of combinations of different start times for the critical window (from XX ms pre target onset to XX ms post target word onset) and window lengths (ranging from XX ms to XX ms). For each combination of start time and window length, we fit a linear mixed-effects model predicting proportion target looking from age, including random intercepts for participants and words. Since observations were unevenly distributed across the age range, we also split our data into three age bins (12-24 months; 24-36 months; 36-48 months).

Figure 5 visualizes the results of the multiverse analysis, visualizing the coefficient estimate and its associated p-value for each combination of window start time and window length. As expected, proportion target looking increases with age within each age time bin (as indicated by a positive coefficient estimate). The analysis shows that the central effect of age on proportion target looking emerges under a wide range of window choices. Intriguingly, each age range shows its own “hot spot” in terms of the largest effects: upper right for 12-24 mos, bottom middle for 24-36 mos, and bottom right for 36-48 mos. This suggests that researchers may be justified in using different start times and window sizes for different age ranges, likely due to the varying pull of familiarity and novelty as learners age.

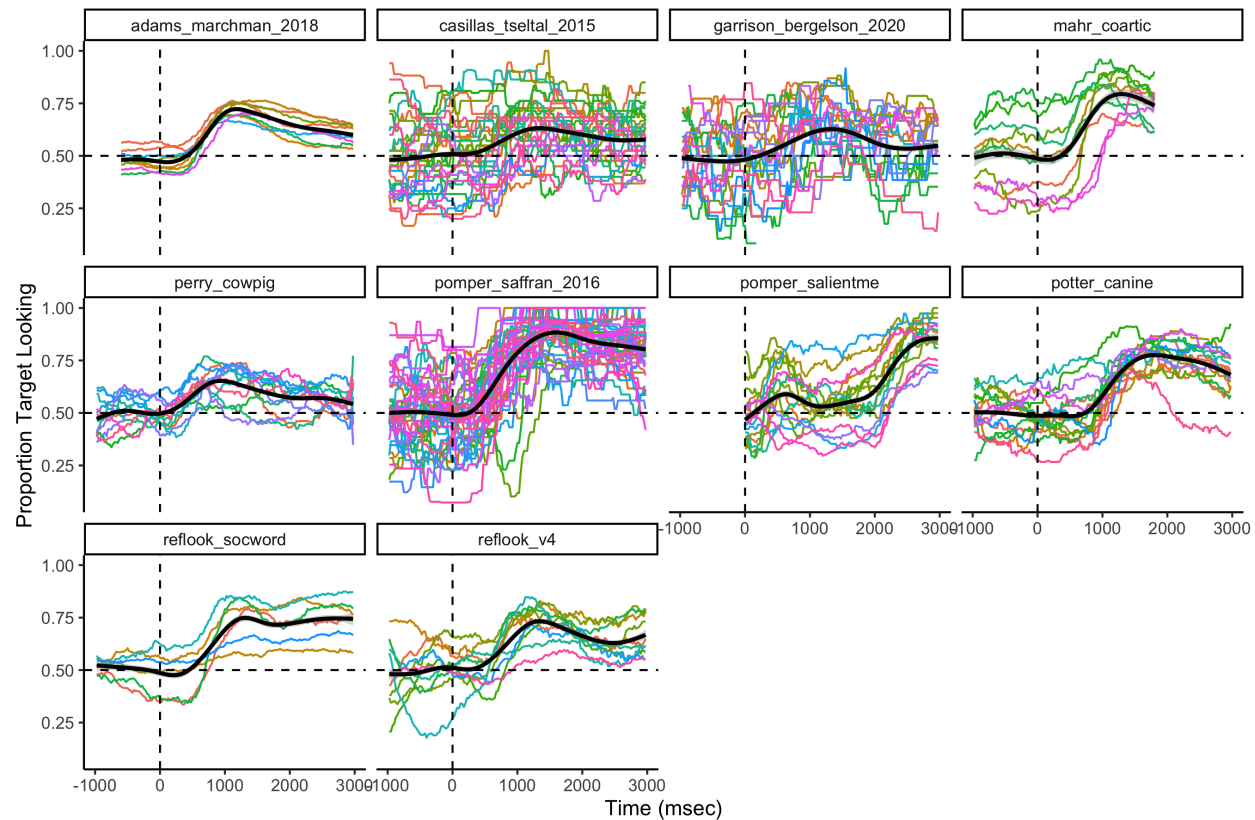


Figure 3: Item-level variability in proportion target looking within each dataset. Colored lines represent specific target labels.

## Discussion

Many central questions in developmental science face a fundamental data collection challenge: Studying effects of interest requires a large amount of observations, but collecting infant data is difficult, time-intensive, and often limited to a small number of observations per participant. Recent years have seen a growing effort to build open source tools and pooling research efforts to meet the challenge of data collection and aggregation in developmental science (Bergmann et al., 2018; The ManyBabies Consortium, 2020). Peekbank expands on these efforts by building an infrastructure for aggregating eyetracking data across studies, with a particular focus on the looking-while-listening paradigm. This paper presents a preliminary illustration of some of the key theoretical and methodological questions the peekbank database aims to address: understanding item-level variability in children's lexical processing and providing data-driven guidance on methodological choices.

Diving into more specifics

Future directions and limitations

limitations in language background (almost entirely English, monolingual)

limitations in participant background (almost entirely WEIRD participants)

growing the database will address these questions while increasing our power to answer the key generalization questions

of interest

expanding beyond child lexical processing: tools and infrastructure can in principle be expanded to accommodate any eyetracking paradigm used with infants and toddlers

## Acknowledgements

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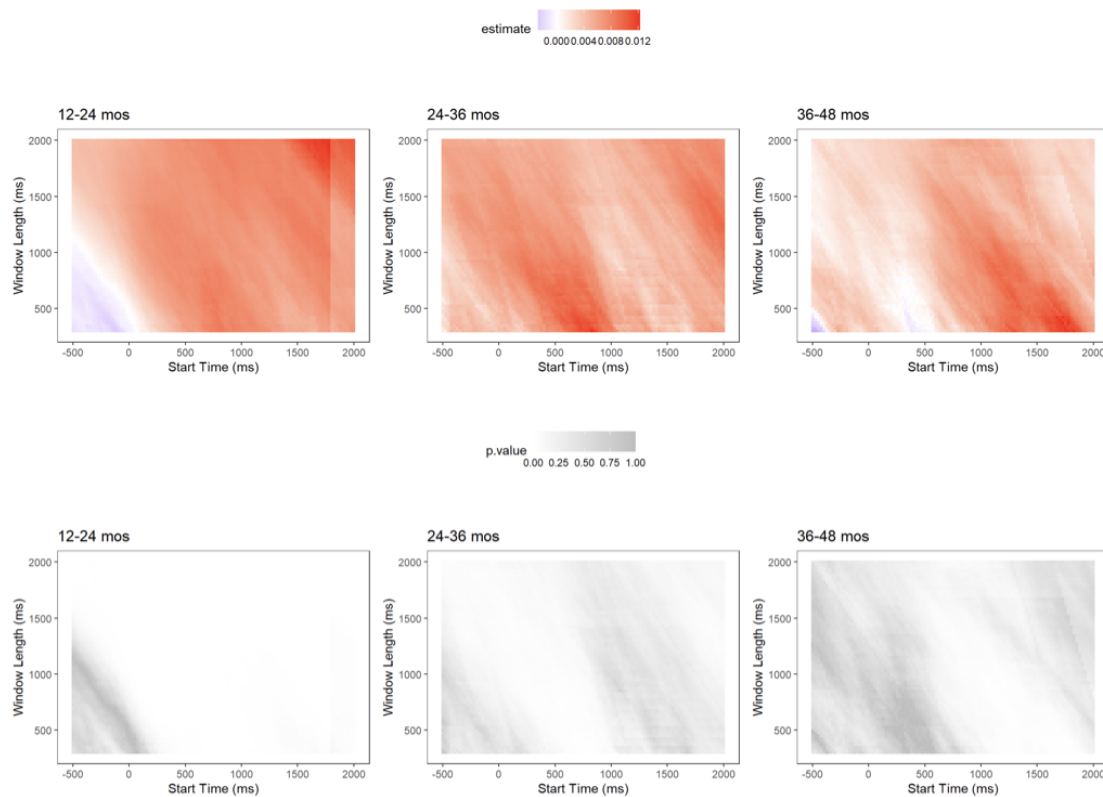


Figure 5: Time window analysis.

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