

Exploring Vocabulary Acquisition in Children*

Predicted Vocabulary Growth in Children: Higher Probabilities for Common Words and Greater Variability in Complex Categories

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First sentence. Second sentence. Third sentence. Fourth sentence.

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*Code and data are available at: https://github.com/Cassieliu77/Vocabulary_Learning_Pattern.git

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1 Introduction

Understanding how children acquire vocabulary is a cornerstone of developmental linguistics and early childhood education. Vocabulary growth is not only a key indicator of cognitive development but also serves as a foundation for future linguistic and academic success. The interplay of factors such as age, linguistic environments, and word categories influences children's vocabulary acquisition in complex and dynamic ways. By analyzing patterns and predictors of vocabulary growth, researchers can uncover insights into the developmental trajectories that shape language learning.

This study leverages a dataset derived from the Wordbank database, which compiles data from the MacArthur-Bates Communicative Development Inventories (CDI), to examine vocabulary

development in children aged 16–30 months. A logistic regression model was employed to predict the likelihood of achieving a high vocabulary score based on variables such as age, norming status, and lexical categories. The model provides a framework for exploring how these predictors interact to shape children’s vocabulary acquisition.

Key findings from this analysis reveal that vocabulary acquisition follows distinct trajectories across different word categories, with age being the strongest predictor of vocabulary growth. Furthermore, categories such as “Living Things” and “Function Words” show consistent acquisition patterns, while others, like “Sensory Words,” exhibit greater variability. These results contribute to a deeper understanding of the linguistic milestones that mark early childhood and highlight areas for further exploration in language development research.

The remainder of this paper is structured as follows: Section 2 describes the dataset, highlighting the variables used and their distributions. Section 3 provides an overview of the logistic regression model and its assumptions. Section 4 presents the results, including variability in vocabulary acquisition, the role of predictors, and predicted probabilities. Finally, Section 5 discusses the implications of the findings and outlines limitations and directions for future research. The data used in this study all comes from Braginsky (2024), and the whole paper is conducted and analyzed in R Core Team (2023).

2 Data

2.1 Overview

The original dataset was obtained from Braginsky (2024). After undergoing a thorough cleaning process—including grouping related items and removing missing values—the analysis focuses on the key variables: category, age, comprehension, production, is_norming, and broad_category. These variables form the foundation of the analysis dataset. An overview of the cleaned dataset is presented in Table 1.

Table 1: Cleaned Word Bank Dataset

Language	Age	Is_Norming	Broad_Category	Production	High_Vocabulary
English (American)	25	FALSE	Sensory Words	658	1
English (American)	26	FALSE	Sensory Words	552	1
English (American)	24	FALSE	Sensory Words	504	1
English (American)	26	FALSE	Sensory Words	272	0
English (American)	24	FALSE	Sensory Words	350	1
English (American)	25	FALSE	Sensory Words	580	1
English (American)	22	FALSE	Sensory Words	351	1
English (American)	24	FALSE	Sensory Words	310	1
English (American)	25	FALSE	Sensory Words	257	0

Table 1: Cleaned Word Bank Dataset

Language	Age	Is_Norming	Broad_Category	Production	High_Vocabulary
English (American)	26	FALSE	Sensory Words	188	0

2.2 Measurement

2.2.1 Data Collection and Quality Control

The objective of measurement in this study is to translate raw parental reports into reliable indicators of vocabulary acquisition patterns in children. The data is derived from the MacArthur-Bates Communicative Development Inventories (CDI), a widely used tool that collects information on children's vocabulary comprehension and production through structured parental surveys. These surveys allow parents to report on their child's understanding and use of specific words, grouped into lexical categories such as nouns, verbs, and adjectives. The raw data collected through the CDI forms the basis for creating the study's dependent and independent variables.

- Structured Response Formats: The CDI employs predefined response options for comprehension and production, reducing ambiguity and enhancing consistency in parental reporting.
- Words Categorization: Vocabulary items are grouped into meaningful lexical categories, allowing for a more nuanced understanding of children's vocabulary development across different word types.
- Norming Group Comparison: The inclusion of norming groups as benchmarks helps to ensure the validity of reported vocabulary scores and allows for cross-child comparison. These groups provide a standardized reference for analyzing individual differences in language acquisition.
- Variable Standardization: Continuous variables, such as age, are standardized (e.g., scaled) to reduce variability and improve the interpretability of statistical models. This ensures that coefficients reflect meaningful changes in relation to standardized measures.
- Bias Mitigation: By structuring responses and including norming benchmarks, the CDI minimizes some of the biases inherent in self-reported data, such as over- or underestimation by parents.
- Missing Data Handling: Observations with incomplete or invalid responses were excluded from the analysis to maintain the integrity and reliability of the dataset.

2.2.2 Reporting Bias

However, there are several considerations regarding the data collection process:

- Parental Reporting Bias: The reliance on parental reports introduces the potential for bias, including overestimation or underestimation of a child's abilities. This is inherent to self-reported data and can affect the accuracy of the results.

- Standardized Format and Structure: The CDI employs predefined response categories, which help to minimize ambiguity in reporting and ensure consistency across respondents. This structured approach mitigates some reporting variability but may not fully capture nuances in vocabulary acquisition.
- Norming Group Representation: To improve validity, a subset of children from norming groups is included as a benchmark for comparison. While useful, this raises concerns about whether the norming group adequately represents the population's diversity in language development.
- Temporal Limitations: The CDI data represents snapshots of vocabulary development at specific ages, which may not account for rapid changes or variations over time in a child's language acquisition process.

Despite its standardized structure, the CDI is subject to biases inherent in parental reporting, including over or underestimation bias. Parents may unintentionally overestimate or underestimate their child's skills due to subjective perceptions or limited observations. Social Desirability Bias: Responses may be influenced by parents' desire to portray their child's language development favorably.

2.3 Outcome Variable

2.3.1 High Vocabulary Score

The outcome variable in this study, High Vocabulary Score, is a binary indicator designed to identify individuals with advanced vocabulary proficiency. This variable is derived from two key measures:

1. Comprehension: This variable represents the ability to understand words and phrases, reflecting the receptive language skills of individuals. Comprehension scores are numerical and vary across the dataset.
2. Production: This variable captures the ability to produce words, reflecting expressive language skills. Like comprehension, production scores are numerical and provide the standard into verbal articulation capabilities.
3. The High Vocabulary Score is calculated using the average of comprehension and production scores for each individual. This average is represented as:
$$\text{prod_comp_mean} = \frac{\text{Comprehension} + \text{Production}}{2}$$

To classify individuals, a threshold value of 300 is applied to `prod_comp_mean`: - Individuals with `prod_comp_mean > 300` are classified as having a high vocabulary score (`outcome = 1`). - Those with `prod_comp_mean <= 300` are classified as not having a high vocabulary score (`outcome = 0`).

This approach ensures that both receptive (comprehension) and expressive (production) skills are considered in defining advanced vocabulary. The threshold of 300 was chosen based on exploratory analysis of the dataset, reflecting a meaningful distinction between individuals with high and low vocabulary abilities. The High Vocabulary Score serves as the dependent variable in the following data analysis part. Its binary nature makes it suitable for modeling with a binomial family distribution, allowing for the estimation of factors that influence advanced vocabulary acquisition.

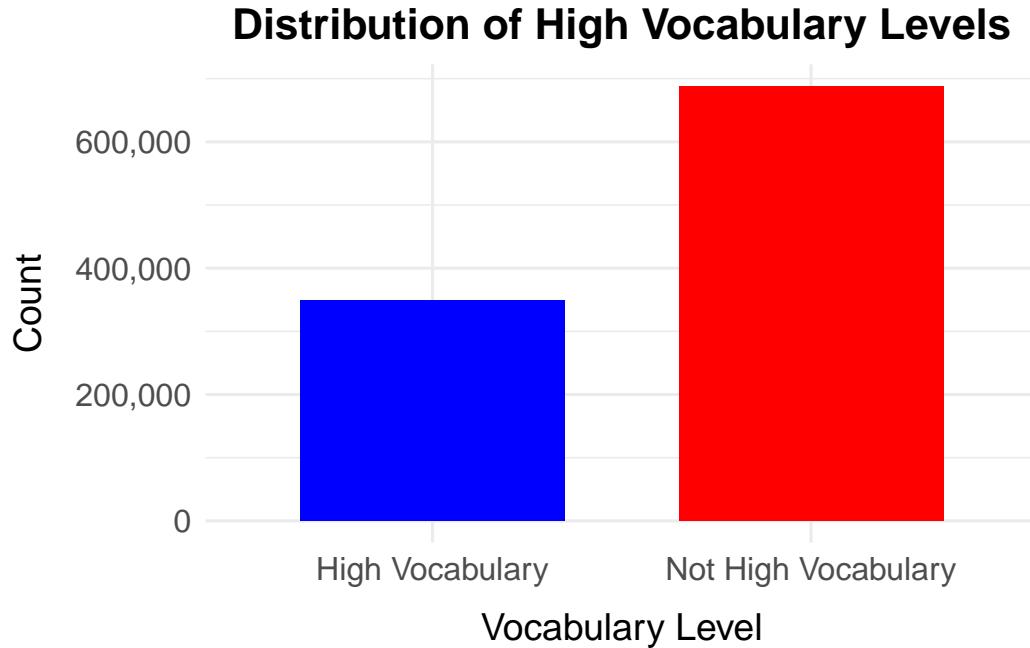


Figure 1: Distribution of the outcome variable, showing the counts of children classified as having “High Vocabulary” and “Not High Vocabulary” based on their comprehension and production scores. The bar plot illustrates the balance between the two categories in the dataset, which is important for modeling purposes.

2.4 Predictor variables

2.4.1 Age

Figure 2 displays the distribution of children’s ages (in months) within the dataset, highlighting key patterns in the sample’s demographic structure. A notable concentration of data is observed among children aged between 24 and 30 months, reflecting an emphasis on capturing vocabulary development during critical periods of language acquisition. These age ranges are known to mark significant milestones in linguistic growth, which could explain their higher representation. Conversely, younger age groups (below 20 months) are underrepresented, likely

due to the challenges of assessing vocabulary at earlier stages of development, where verbal communication is less pronounced and parental reporting is more variable.

The dataset also shows distinct peaks at specific ages, such as 25 and 30 months. These sharp spikes may reflect intentional focus points for testing or developmental benchmarks tied to standardized assessments like the MacArthur-Bates Communicative Development Inventories (CDI). This uneven age distribution underscores the importance of age as a critical factor in analyzing vocabulary acquisition. While the high concentration of data at older ages enhances insights into advanced vocabulary development, it also necessitates caution in generalizing findings to underrepresented age groups. This observation emphasizes the need to standardize age in statistical models to account for variability across different age groups.

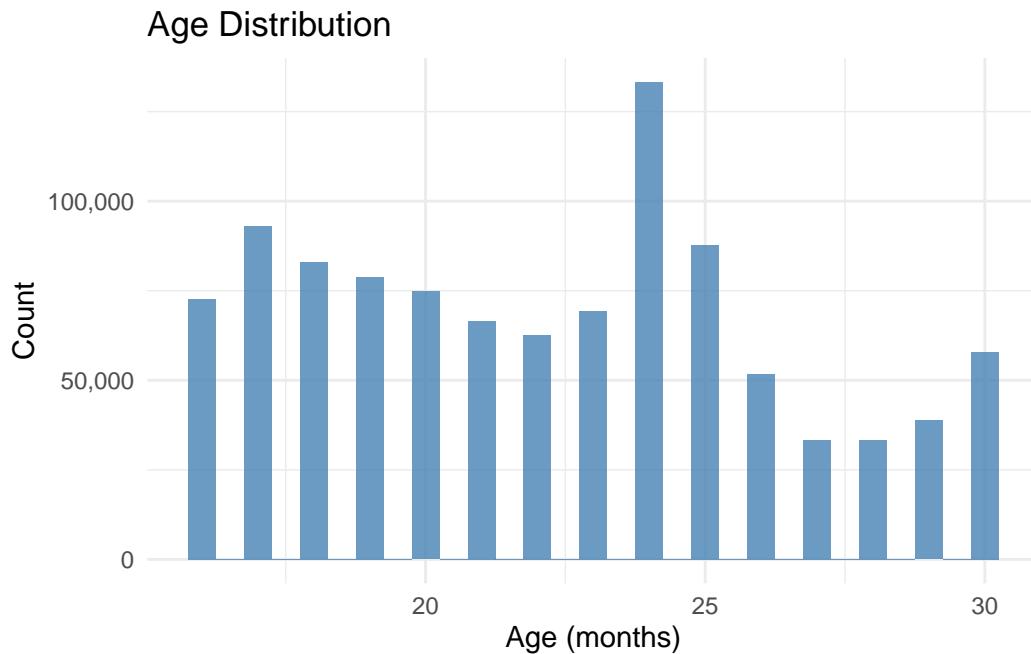


Figure 2: It shows the distribution of children’s ages (in months) within the dataset. The majority of observations fall between 24 and 30 months, with noticeable peaks at 25 and 30 months, reflecting a focus on key developmental periods. Younger age groups are underrepresented, highlighting the need to account for variability in age when analyzing vocabulary acquisition patterns.

2.4.2 Broad Category

The words in the dataset were grouped into broad lexical categories to facilitate the analysis of vocabulary acquisition patterns. These categories include Activities, Adjectives, Function Words, Living Things, Objects, Places, Sensory Words, and Verbs. The classification was

based on the semantic and functional roles of words, with nouns subdivided into more specific groups such as Living Things, Objects, and Places to capture distinct trends in vocabulary acquisition. For instance, Function Words include pronouns and question words, reflecting grammatical development, while Verbs and Adjectives capture action and descriptive words, essential for sentence construction and expression.

The bar graph illustrates the distribution of items across these categories, highlighting significant variation in word frequency. Objects constitute the largest category, suggesting a focus on tangible and concrete items, which are likely easier for children to recognize and recall. This is followed by Verbs and Living Things, categories that are fundamental to communication but slightly less prevalent. In contrast, Sensory Words and Activities are sparsely represented, possibly reflecting their specialized and context-dependent nature. The distribution underscores the importance of concrete and functional words in early vocabulary development while highlighting potential gaps in underrepresented categories. This variation provides a foundation for exploring how lexical diversity influences vocabulary acquisition patterns.

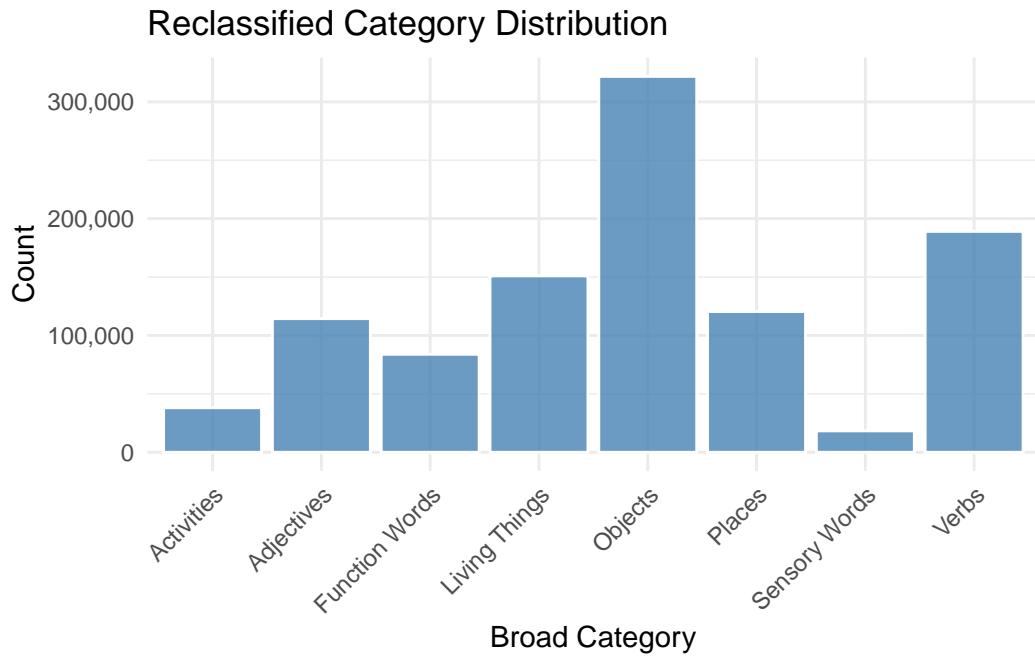


Figure 3: The figure shows objects dominate the vocabulary, reflecting an emphasis on concrete and tangible terms, while categories like Sensory Words and Activities are less frequently represented, indicating the relative complexity or specificity of these word types in early language acquisition

2.4.3 Norming Status

The `is_norming` variable categorizes children into two groups: the norming group and the non-norming group. The norming group serves as a standardized sample, providing a benchmark for assessing vocabulary development and enabling reliable comparisons across the dataset. This group is essential for ensuring the validity of the analysis by offering a consistent reference point for evaluating individual and group-level differences in vocabulary acquisition.

The dataset is predominantly composed of non-norming children, with only a small proportion belonging to the norming group. This imbalance reflects the inherent challenges of including a sufficiently broad and representative norming sample in large-scale assessments. While the non-norming group captures diverse linguistic and demographic contexts, the norming group remains vital for calibrating and interpreting vocabulary development patterns, particularly in early language acquisition studies. Table 2 illustrates this distribution, highlighting the predominance of non-norming children in the dataset.

The `is_norming` variable is included in the logistic regression model to account for potential systematic differences between the norming and non-norming groups. As the norming group represents a standardized sample used as a benchmark for vocabulary development, its inclusion ensures that variations in the likelihood of achieving a high vocabulary score are not confounded by differences in group composition or assessment protocols. It allows the model to estimate whether membership in the norming group significantly influences vocabulary acquisition outcomes. This is particularly important given the inherent imbalance in the dataset, where the non-norming group constitutes the majority. By controlling for `is_norming`, the model can differentiate between developmental patterns attributable to broader population diversity versus those arising from the structured selection of the norming sample.

Table 2: The dataset is primarily composed of non-norming children, with a smaller subset belonging to the norming group, serving as a standardized benchmark for assessing vocabulary development

Table 2: Summary of Norming Status in the Dataset

Norming Status	Count
FALSE	1031560
TRUE	5440

3 Model

3.1 Model Selection

To investigate the relationship between children's vocabulary acquisition and their demographic and linguistic characteristics, we constructed a logistic regression model. By examining key demographic and linguistic predictors, we aim to identify how characteristics like age, norming status, and word categories influence vocabulary development. The dependent variable, `high_vocabulary`, is a binary outcome indicating whether a child's average production and comprehension score (denoted as `prod_comp_mean`) exceeds 300. This threshold was chosen to distinguish children with relatively advanced vocabulary levels. More background details and diagnostics are included in Appendix- [B](#).

3.2 Logistic Regression Model Overview

- High Vocabulary: A binary indicator where 1 represents a high vocabulary score (combined comprehension and production > 300), and 0 otherwise.
- Scaled Age (`age_scaled`): The child's age, standardized to reflect changes per standard deviation. Standardization aids in interpretability and ensures numerical stability.
- Norming Status (`is_norming`): A binary indicator denoting whether a child is part of the norming dataset (TRUE) or not (FALSE). This variable accounts for potential differences in data collection or assessment protocols.
- Broad Category (`broad_category`): A categorical variable grouping words into lexical categories, such as adjectives, verbs, and nouns. The reference category for comparison is Function Words.

The model is specified as:

$$\log \left(\frac{p_i}{1 - p_i} \right) = \beta_0 + \beta_1 \cdot \text{age_scaled}_i + \beta_2 \cdot \text{is_norming}_{\text{TRUE}_i} \quad (1)$$

$$+ \beta_3 \cdot \text{broad_categoryAdjectives}_i \quad (2)$$

$$+ \beta_4 \cdot \text{broad_categoryFunction_Words}_i \quad (3)$$

$$+ \beta_5 \cdot \text{broad_categoryLiving_Things}_i \quad (4)$$

$$+ \beta_6 \cdot \text{broad_categoryObjects}_i \quad (5)$$

$$+ \beta_7 \cdot \text{broad_categoryPlaces}_i \quad (6)$$

$$+ \beta_8 \cdot \text{broad_categorySensory_Words}_i \quad (7)$$

$$+ \beta_9 \cdot \text{broad_categoryVerbs}_i \quad (8)$$

Where: - p_i represents the probability that child i has a high vocabulary score - β_0 is the intercept, capturing the baseline log-odds when all predictors are at their reference or mean levels - β_1 : Effect of age (standardized) - β_2 : The effect of whether the individual belongs to the norming group - $\beta_3, \beta_4, \beta_5$, etc.: The effects of being in the respective broad word categories (nouns, function words, or verbs), compared to the reference category (likely “adjectives”).

3.3 Model Assumptions

- Linearity of the Logit: The model assumes a linear relationship between the log-odds of the outcome (high vocabulary) and the independent variables. For example, the standardized age variable (age_scaled) reflects that for every one standard deviation increase in age, the log-odds of achieving a high vocabulary score change by a constant amount. Standardizing age ensures that the variable is centered around zero and scaled to have a standard deviation of one, which not only aids interpretability but also supports the linearity assumption across the dataset.
- Independence of Observations: Each observation in the dataset is assumed to be independent. This assumption holds because each data point corresponds to a unique child, with no repeated measures or nested structures, such as clustering by classrooms or schools. If there were dependencies (e.g., repeated measures for the same child or hierarchical data), a mixed-effects logistic regression or another hierarchical model would be required to account for these correlations.
- Categorical Variable Encoding: The broad_category variable, which classifies words into categories such as “Adjectives,” “Verbs,” and “Living Things,” is encoded using sum contrasts. This encoding ensures that the coefficients for each category represent its deviation from the overall mean effect across all categories. For example, the coefficient for “Verbs” reflects the difference in log-odds of achieving a high vocabulary score for words in the “Verbs” category compared to the average log-odds across all categories. Using sum contrasts ensures that the model’s intercept represents the overall mean effect when all predictors are at their reference or average levels, facilitating meaningful interpretation of the model coefficients.
- Binary Nature of the Outcome: The dependent variable, high_vocabulary, is binary (1 = high vocabulary, 0 = not high vocabulary). Logistic regression is specifically designed for binary outcomes, and the binomial distribution of the data supports the appropriateness of the logistic framework.
- No Perfect Multicollinearity: The model assumes that the predictors are not perfectly correlated with one another. High multicollinearity could distort coefficient estimates, making it difficult to interpret the unique contribution of each variable. Steps such as standardizing continuous predictors and carefully encoding categorical variables mitigate this risk.

3.4 Interpretation of Coefficients

The logistic regression coefficient (β) represents the change in the log-odds of the dependent variable (high vocabulary) for a one-unit change in the predictor variable, holding all other variables constant.

- Intercept (β_0): Represents the log-odds of high vocabulary when all predictors are at their reference or mean levels. If $\beta_0 > 0$, the baseline odds of high vocabulary are greater than 50%.
- Scaled Age (β_1): For each one standard deviation increase in age, the log-odds of high vocabulary increase by β_1 . If $\beta_1 = 0.5$, then $\exp(0.5) \approx 1.65$, meaning the odds increase by 65% for every one standard deviation increase in age.
- Norming Status (β_2): If a child belongs to the norming group, the log-odds of high vocabulary increase by β_2 compared to non-norming children. If $\beta_2 = 0.1$, then $\exp(0.1) \approx 1.11$, meaning being in the norming group increases the odds of high vocabulary by 11%.
- Broad Category ($\beta_3, \beta_4, \beta_5$, etc.): The coefficients for `broad_category` represent the difference in log-odds compared to the reference category (“Adjectives”).
 - β_3 (Function Words): A positive β_3 indicates higher odds of having a high vocabulary for function words compared to adjectives. For instance, if $\beta_3 = 0.002$, then $\exp(0.002) \approx 1.002$, meaning the odds of having a high vocabulary for function words are 0.2% higher than for adjectives. General Example for Broad Categories: If a coefficient $\beta_k = 0.01$, $\exp(0.01) \approx 1.01$, meaning the corresponding category increases the odds of having a high vocabulary by 1% compared to the reference category (Adjectives). Conversely, if $\beta_k = -0.01$, $\exp(-0.01) \approx 0.99$, indicating a 1% decrease in odds compared to the reference category.

3.5 Model Justification

Logistic regression is widely used in predictive modeling for categorical outcomes due to its simplicity and robustness. It provides probabilities that are constrained between 0 and 1, ensuring meaningful interpretations for binary outcomes. Unlike other complex models, logistic regression allows for clear coefficient interpretation, offering insights into the magnitude and direction of predictor effects. For example, the odds ratios derived from logistic regression help explain how changes in variables like age or norming status influence the probability of high vocabulary acquisition.

Although advanced machine learning models like decision trees, random forests, or neural networks could be used, these methods often lack the interpretability of logistic regression. While these models might yield slightly better predictive performance, they are often considered “black boxes,” making it difficult to identify specific relationships between predictors and outcomes. Given the study’s focus on understanding developmental patterns rather than maximizing predictive accuracy, logistic regression is more appropriate.

Moreover, complex models require larger datasets to avoid overfitting and ensure generalizability, which might not be feasible given the sample size and the structure of the data in this study. Logistic regression strikes a balance between simplicity, interpretability, and predictive performance.

The dataset was split into training and testing subsets to ensure model validation and reduce overfitting. This allows the model to generalize better to unseen data, providing a more reliable assessment of its predictive accuracy. Standardizing continuous predictors, such as age, enhances interpretability and ensures that variables are on a comparable scale, preventing dominance by predictors with larger numerical ranges.

To ensure reproducibility, the preprocessed datasets and the trained model were saved. This practice facilitates verification of results and supports future analyses or extensions of the study. Overall, the logistic regression model offers a clear and interpretable framework for investigating vocabulary acquisition patterns, providing both explanatory power and practical insights.

4 Results

4.1 Variability in Production Vocabulary

Figure 4 visualizes the relationship between age and production vocabulary scores, focusing on different percentiles of the distribution. The scatterplot shows individual production scores as gray dots, while overlaid lines represent percentiles (10th, 25th, 50th, 75th, and 90th), capturing central tendencies and variability across ages. The 50th percentile (median) line provides a benchmark for the typical vocabulary production score at each age, whereas the 10th and 90th percentiles outline the lower and upper ranges of vocabulary development. The gradual upward trend of the median line reflects consistent growth in production vocabulary as children age, with a widening gap between the percentiles at later ages. This widening suggests increasing variability in vocabulary acquisition, with some children advancing much faster than others in production abilities.

The data indicates that children in the 90th percentile acquire vocabulary at a significantly faster rate than their peers, as evidenced by the steeper slope of the topmost line. Conversely, the 10th and 25th percentiles show more gradual, stable growth, suggesting slower development for children in these groups. The broader range of scores at older ages emphasizes the heterogeneity of developmental trajectories, with some children reaching vocabulary sizes substantially larger than the median while others remain below average. These findings underscore the diversity in early language acquisition and highlight the importance of considering individual differences when evaluating children's vocabulary development.

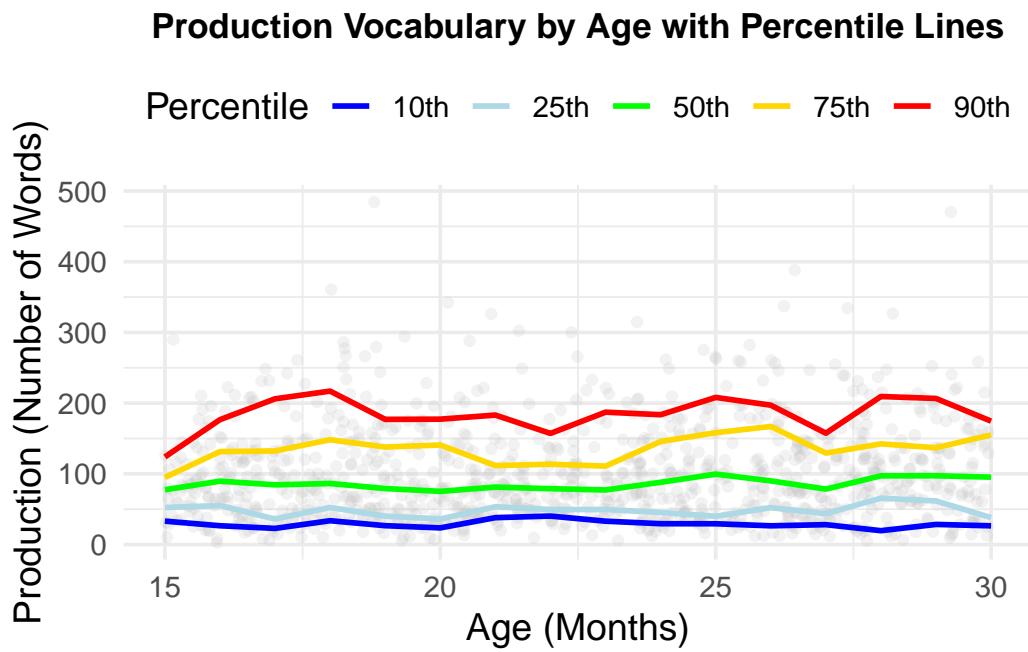


Figure 4: Production Vocabulary by Age with Percentile Lines. The graph illustrates the production scores of children across different ages (in months). Individual data points (gray dots) represent raw production scores for each participant. Colored lines correspond to standardized percentiles—10th (blue), 25th (light blue), 50th (green), 75th (yellow), and 90th (red)—showing trends in vocabulary production distribution over time.

4.2 Median Vocabulary Size Change by Age

Figure 5 illustrates the median comprehension vocabulary scores across different ages, focusing on the central tendency of children's comprehension development between 15 and 30 months. The gray dots represent individual data points, capturing the variability in comprehension scores, while the blue line highlights the median score for each age group. The graph shows a clear upward trajectory, with median comprehension steadily increasing with age, particularly after 18 months. This suggests a critical developmental period between 18 and 30 months during which children experience significant growth in comprehension vocabulary. The density and spread of gray points around the median line indicate individual variability, emphasizing that while the general trend is one of growth, some children exhibit slower or faster development compared to their peers. The visualization underscores the importance of age as a determinant of vocabulary comprehension while highlighting the diverse range of learning patterns among children.

Steady Growth in Comprehension Vocabulary: Between 15 and 18 months, the median comprehension score remains relatively stable, indicating slower growth in vocabulary during early stages of language acquisition. A noticeable increase in vocabulary size is observed after 18 months, suggesting that children begin to acquire words more rapidly as their cognitive and linguistic abilities develop. The most significant growth occurs between 24 and 30 months, where the median comprehension score consistently rises. This period aligns with critical developmental milestones, such as the expansion of receptive language and comprehension skills. The distribution of points (grey scatter) highlights considerable variability in comprehension scores at each age. While the median line captures the central trend, some children show significantly higher or lower comprehension compared to their peers, reflecting individual differences in language learning rates. Around 30 months, the upward slope of the median line begins to level off slightly, suggesting that comprehension growth may slow down or stabilize as children approach the end of the observed range.

The use of the median instead of the mean ensures that the central trend is not skewed by outliers (e.g., extremely high or low comprehension scores). This choice provides a robust summary of comprehension at each age, especially in datasets with large variability or non-normal distributions. These findings highlight the critical window between 21 and 26 months for comprehension vocabulary growth. Interventions or language exposure strategies during this period may be particularly effective in enhancing language development. The observed variability suggests that individual-level factors (e.g., family environment, exposure to language) play a significant role in shaping comprehension scores, warranting further investigation into these influences.

4.3 Predictiton for the Probability of High Vocabulary Level

```
# A tibble: 176 x 4
  age broad_category is_norming mean_predicted_prob
```

Median Comprehension Vocabulary by Age (Resampled)

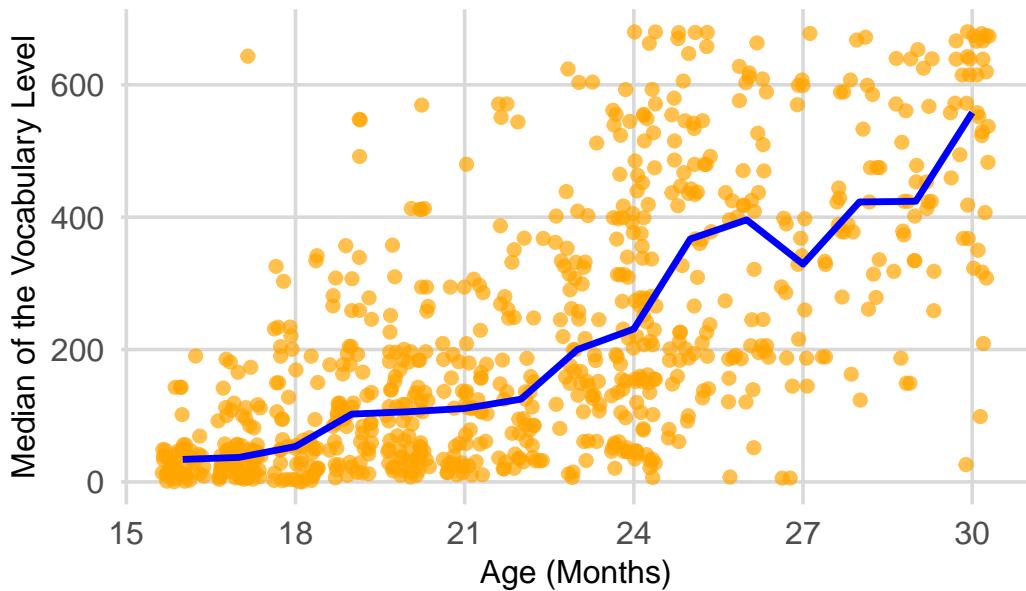


Figure 5: Illustrating central tendencies in comprehension vocabulary scores based on resampled data

```

<int> <fct>      <lgl>          <dbl>
1   16 Activities FALSE 0.0303
2   16 Adjectives FALSE 0.0305
3   16 Function Words FALSE 0.0305
4   16 Living Things FALSE 0.0305
5   16 Objects FALSE 0.0302
6   16 Places FALSE 0.0301
7   16 Sensory Words FALSE 0.0299
8   16 Verbs FALSE 0.0304
9   17 Activities FALSE 0.0444
10  17 Adjectives FALSE 0.0446
# i 166 more rows

# A tibble: 2 x 2
  is_norming overall_mean_prob
  <lgl>          <dbl>
1 FALSE           0.394
2 TRUE            0.724

```

4.4 Predicted Probabilities by Age

Figure 6 illustrates the relationship between predicted probabilities of achieving high vocabulary and age, with percentile trends (10th, 25th, 50th, 75th, and 90th percentiles) overlaid to highlight the variability in predictions. The scatterplot points represent individual predicted probabilities, while the percentile lines depict the progression of predictions across age groups.

The median predicted probability (50th percentile, solid blue line) steadily increases with age, reflecting the model's growing confidence in high vocabulary acquisition as children get older. The 10th and 25th percentiles (dashed and dotted red/purple lines) remain relatively low at younger ages but show a notable rise after 20 months, suggesting greater variability in predictions among younger children. In contrast, the 75th and 90th percentiles (dashed and dotted purple/red lines) start higher and climb more sharply, indicating that some children exhibit advanced vocabulary skills even at younger ages.

Overall, the increasing spread between the percentile lines with age highlights a broader range of vocabulary acquisition patterns as children develop. This visualization underscores the model's ability to account for individual differences in learning trajectories while confirming the strong association between age and predicted probability of high vocabulary.

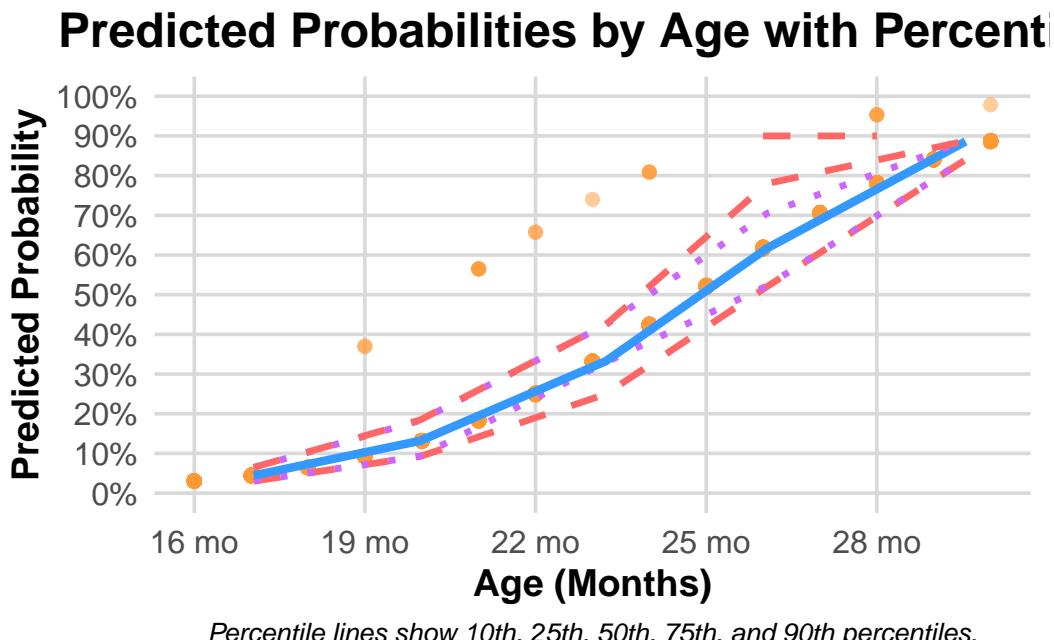


Figure 6

4.5 Distribution of Predicted Probabilities by Category

The distribution of predicted probabilities for achieving high vocabulary varies across word categories, as shown in Figure 7. Categories such as Function Words, Living Things, and Objects demonstrate a concentration of predicted probabilities closer to 0.5 or above, indicating the model's moderate to high confidence in associating these categories with vocabulary acquisition. These categories likely reflect simpler or more frequently used words that children acquire earlier. In contrast, categories like Sensory Words and Verbs exhibit a higher density of lower predicted probabilities, suggesting that these words are more challenging for children to acquire or are less common in early vocabularies.

Some categories, such as Adjectives and Places, display broader distributions of predicted probabilities, spanning from low to high values. This variability may reflect differences in children's exposure to or use of these word types, as well as greater heterogeneity in language environments. Overall, these findings provide insights into how the model predicts vocabulary acquisition and highlight the influence of word category. Categories with more focused distributions (e.g., Function Words) suggest consistent acquisition patterns, while those with broader spreads (e.g., Verbs) point to areas where model predictions are less certain and could benefit from further refinement.

5 Discussion

5.1 Age and Developmental Trajectories

The findings emphasize age as the most influential predictor of vocabulary acquisition. The sharp increase in predicted probabilities as children grow older aligns with expectations, as the developmental window between 18 and 30 months is crucial for rapid language learning. The steady upward trend in median vocabulary probabilities suggests that this period is marked by consistent growth in both production and comprehension. However, the growing variability between the upper and lower percentiles reveals the diverse learning trajectories among children. While some children quickly advance, others may require more time, reflecting the role of environmental factors and individual differences in cognitive development.

Interestingly, the plateauing trend observed in certain facets of comprehension suggests that as children master foundational vocabulary, their acquisition of more complex or context-specific words becomes less predictable. This shift highlights the importance of contextual factors such as exposure to rich language environments and interactions with caregivers.

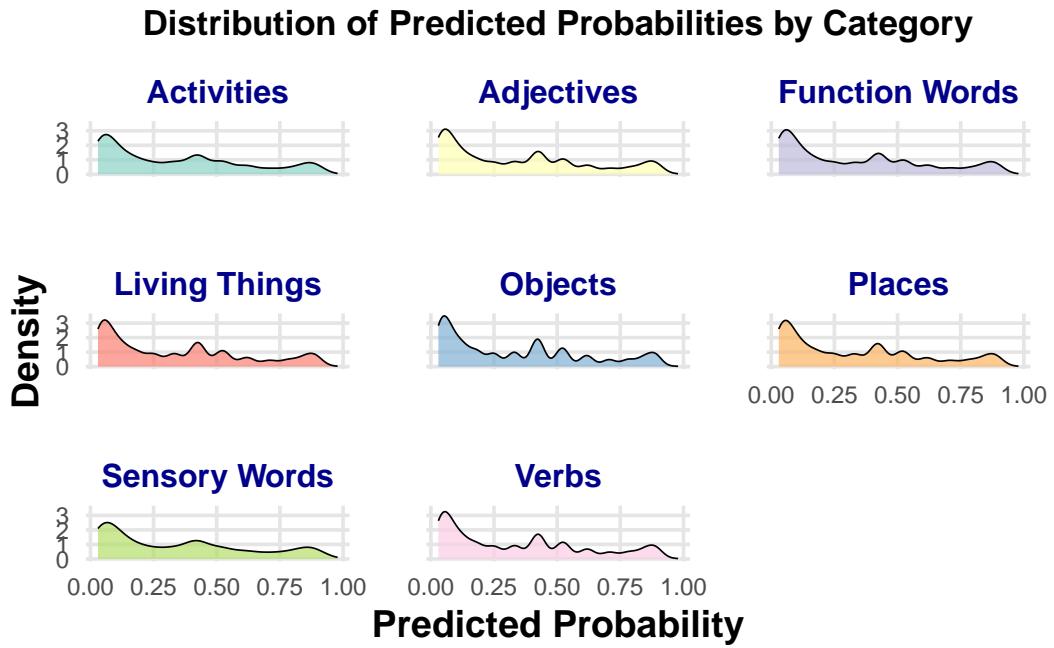


Figure 7: This density plot illustrates the predicted probabilities of having a high vocabulary across different broad lexical categories. Each curve represents the density of predicted probabilities within a category, showcasing the variation in predicted outcomes for categories such as Activities, Adjectives, Function Words, Living Things, Objects, Places, Sensory Words, and Verbs. The plot highlights overlapping patterns and areas of divergence in vocabulary acquisition likelihood across different types of words.

5.2 Word Categories: Foundation and Complexity

The analysis of word categories revealed striking differences in acquisition patterns. Categories such as “Function Words,” “Living Things,” and “Objects” displayed higher predicted probabilities, likely because these words are more frequently encountered in everyday interactions and form the backbone of early communication. In contrast, categories like “Verbs” and “Sensory Words” demonstrated lower probabilities and wider variability, suggesting they are more challenging for young learners. These words often require greater contextual understanding or abstract thinking, which may develop later in the language acquisition process.

The variability in word categories sheds light on how children’s experiences shape their vocabulary. For instance, categories with higher predicted probabilities may reflect a shared baseline of language exposure across children, whereas the broader spread in categories like “Adjectives” or “Sensory Words” points to the influence of specific cultural or environmental factors.

The acceleration in early vocabulary is even clearer when looking at production reports from older children using Words & Sentences. Figure 5.3 shows this pattern. In every language, the median child is reported to produce 50 words between 16–20 months (dotted line), though – as we will see below – this analysis masks tremendous between-child variability during this period. In addition, languages vary considerably in the absolute number of words reported. (As it is a major outlier, we have discussed the Beijing Mandarin WS data in Chapter 3, section on difficult data). Nevertheless, there are still substantial consistencies in the shape and general numerical range across languages.

During the period of 24–30 months, we see curves leveling out. Presumably, this leveling does not reflect a slowing in the rate of acquisition, which most researchers assume continues unabated for many years (e.g., Bloom, Tinker, and Scholnick 2001). Instead, it reflects the limitations of the CDI instrument, in that there are many possible “more advanced” words that children are likely learning, of which only a small subset are represented on any form.

The results highlight distinct trajectories in vocabulary development among children. Production scores showed a steady increase with age, with notable accelerations between 18 and 30 months. This period is critical for vocabulary acquisition, as children rapidly expand their linguistic capabilities. The variability observed in percentile distributions emphasizes individual differences in learning rates, influenced by factors such as exposure to language, socio-economic background, and cognitive abilities.

The analysis of comprehension data revealed a similar trend, with a marked rise in vocabulary comprehension after 18 months. Median comprehension scores provided a robust central tendency, effectively avoiding skewness caused by outliers. The plateau observed around 30 months suggests a stabilization in vocabulary growth, likely reflecting the limitations of the CDI dataset rather than a developmental plateau.

5.3 Broader Implications for Language Development

The findings of this study offer practical applications for early education and language interventions by highlighting specific word categories that are more challenging for children to acquire. For instance, verbs and sensory words, which often require greater contextual understanding, could be emphasized in storytelling, play, and structured educational settings to help bridge the gap in these more complex categories. Tailored approaches in language development programs can address individual learning needs, with children demonstrating slower growth in foundational vocabulary benefiting from increased exposure to high-frequency words. Conversely, those excelling in comprehension may gain from activities introducing less common or context-specific terms, thereby expanding their linguistic repertoire.

Key predictors, including age, norming status, and lexical categories, significantly influenced vocabulary acquisition. Age was the strongest determinant of language growth, with older children showing higher vocabulary scores, consistent with developmental expectations. Additionally, children in the norming group exhibited superior vocabulary acquisition, potentially due to the structured linguistic environments associated with their assessment. Lexical categories provided further insights into vocabulary development, with objects and verbs showing higher predicted probabilities of achieving advanced vocabulary levels, reflecting their functional importance in early communication. In contrast, sensory words and adjectives displayed less consistent patterns, suggesting their acquisition may occur later as children's linguistic abilities become more sophisticated.

5.4 Limitations and Future Directions

264 typically developing Chinese children (145 boys and 119 girls) were included from a longitudinal study of language. While the findings offer valuable insights, several limitations should be acknowledged. First, the reliance on parental reports introduces potential biases, including over- or underestimation of children's abilities. Future studies could complement CDI data with observational or experimental measures to enhance reliability. Second, the cross-sectional nature of the data limits the ability to track individual developmental trajectories. Longitudinal studies are needed to capture within-child variability and the dynamics of vocabulary growth over time. Familial factors and reading or language related cognitive skills were found to be associated with these developmental subgroups.

Future research should also explore the influence of environmental and contextual factors, such as language exposure, educational interventions, and socio-economic status, on vocabulary acquisition. These factors could provide a more comprehensive understanding of the mechanisms underlying linguistic development.

The strongest developmental inferences can be made by the examination of longitudinal data, in which children's individual development is measured multiple times using the same instrument. Unfortunately, relatively little of our CDI data comes from this type of repeated

administration. Figure 3.5 shows the number of administrations for particular languages that come from longitudinal datasets with a particular depth. There is a substantial amount of two-administration longitudinal data for several languages, but only a few have more than two observations for individual children. In general, this aspect of our data is a consequence of the fact that, for normative datasets, pure cross-sectional data collection is used to ensure statistical independence between datapoints. Thus, we must typically settle for using the large amount of available cross-sectional data to average out individual variability.

A Appendix

A.1 This criterion is linked to a Learning OutcomeSurveys, sampling, and observational data appendix

Please include an appendix where you focus on some aspect of surveys, sampling or observational data, related to your paper. This should be an in-depth exploration, akin to the “idealized methodology/survey/pollster methodology” sections of Paper 2. Some aspect of this is likely covered in the Measurement sub-section of your Data section, but this would be much more detailed, and might include aspects like simulation and linkages to the literature, among other aspects.

A.2 Data Sheet

B Model details

B.1 Model Summary

Table 3

	(1)
(Intercept)	-1.014 (0.015)
age_scaled	1.605 (0.004)
is_normingTRUE	1.749 (0.040)
broad_categoryAdjectives	0.006 (0.017)
broad_categoryFunction Words	0.005 (0.018)
broad_categoryLiving Things	0.005 (0.017)
broad_categoryObjects	-0.005 (0.016)
broad_categoryPlaces	-0.008 (0.017)
broad_categorySensory Words	-0.015 (0.026)
broad_categoryVerbs	0.004 (0.016)
Num.Obs.	829 600
AIC	754 890.6
BIC	755 006.9
Log.Lik.	-377 435.316
RMSE	0.39

B.2 Diagnostics

B.2.1 Confusion Matrix

Predicted		
Actual	0	1
0	117737	19871
1	28615	41177

Metric	Value
Accuracy	0.77
Sensitivity (Recall)	0.59
Specificity	0.86
Precision	0.67

B.2.2 ROC Curve and AUC

```
Type 'citation("pROC")' for a citation.
```

```
Attaching package: 'pROC'
```

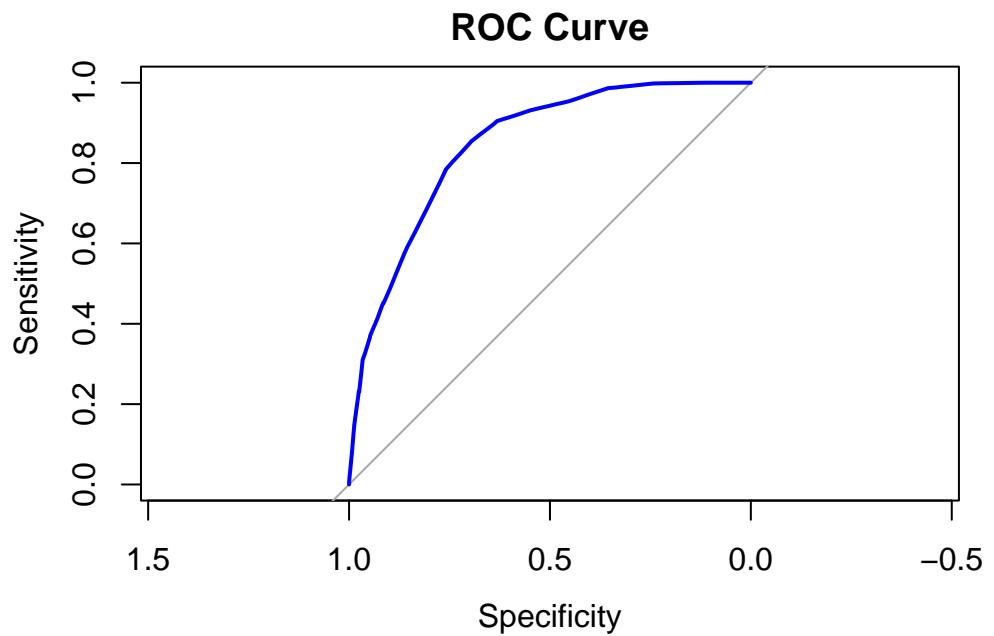
```
The following objects are masked from 'package:stats':
```

```
cov, smooth, var
```

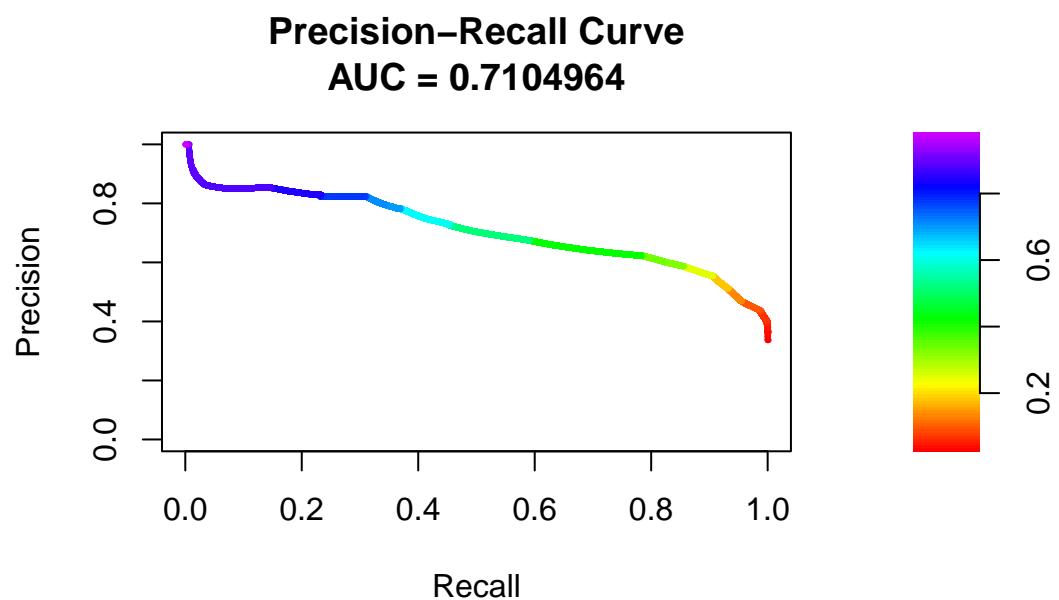
```
Setting levels: control = 0, case = 1
```

```
Setting direction: controls < cases
```

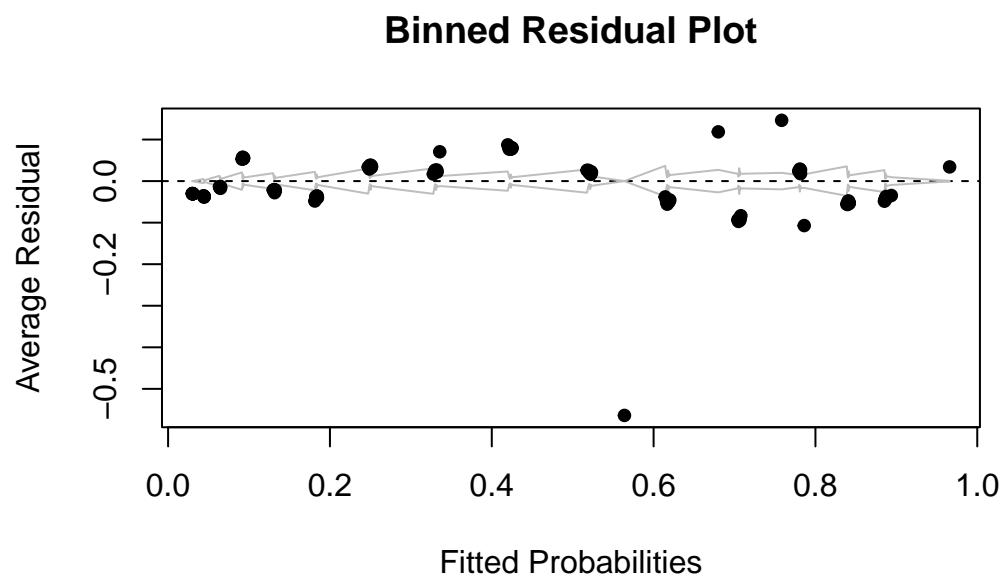
```
AUC: 0.8459010128968
```



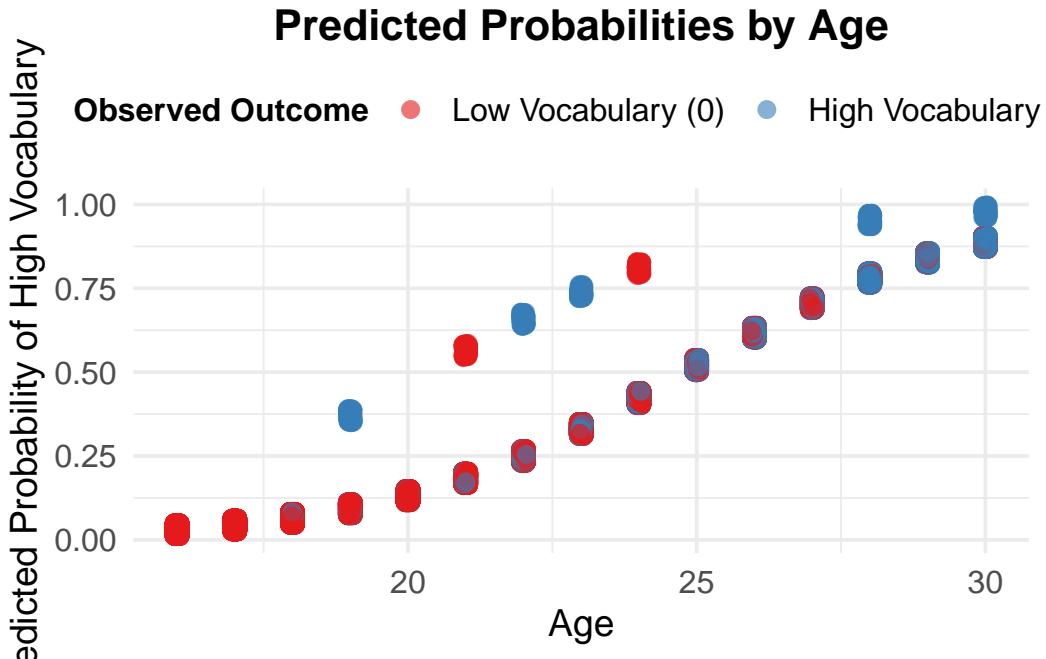
B.2.3 Precision-Recall Curve



B.2.4 Binned Residual Plot



B.2.5 Predicted Probabilities by Age



C Acknowledgements

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References

- Arel-Bundock, Vincent. 2022. “modelsummary: Data and Model Summaries in R.” *Journal of Statistical Software* 103 (1): 1–23. <https://doi.org/10.18637/jss.v103.i01>.
- Braginsky, Mika. 2024. *wordbankr: Accessing the Wordbank Database*. <https://github.com/langcog/wordbankr>.
- Gelman, Andrew, and Yu-Sung Su. 2024. *arm: Data Analysis Using Regression and Multi-level/Hierarchical Models*. <https://CRAN.R-project.org/package=arm>.
- R Core Team. 2023. *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing. <https://www.R-project.org/>.
- Richardson, Neal, Ian Cook, Nic Crane, Dewey Dunnington, Romain François, Jonathan Keane, Dragoş Moldovan-Grünfeld, Jeroen Ooms, Jacob Wujciak-Jens, and Apache Arrow. 2024. *arrow: Integration to 'Apache' 'Arrow'*. <https://CRAN.R-project.org/package=arrow>.
- Wickham, Hadley. 2016. *ggplot2: Elegant Graphics for Data Analysis*. Springer-Verlag New York. <https://ggplot2.tidyverse.org>.
- Wickham, Hadley, Mara Averick, Jennifer Bryan, Winston Chang, Lucy D’Agostino McGowan, Romain François, Garrett Grolemund, et al. 2019. “Welcome to the tidyverse.” *Journal of Open Source Software* 4 (43): 1686. <https://doi.org/10.21105/joss.01686>.
- Wickham, Hadley, Romain François, Lionel Henry, Kirill Müller, and Davis Vaughan. 2023. *dplyr: A Grammar of Data Manipulation*. <https://CRAN.R-project.org/package=dplyr>.
- Wickham, Hadley, Thomas Lin Pedersen, and Dana Seidel. 2023. *scales: Scale Functions for Visualization*. <https://CRAN.R-project.org/package=scales>.
- Wickham, Hadley, Davis Vaughan, and Maximilian Girlich. 2024. *tidyr: Tidy Messy Data*. <https://CRAN.R-project.org/package=tidyr>.
- Xie, Yihui. 2024. *knitr: A General-Purpose Package for Dynamic Report Generation in R*. <https://yihui.org/knitr/>.