

## Background

- Growth failure among preterm infants has been shown to have an impact on poor neurodevelopment outcomes, with the gut microbiota potentially playing an integral role (1).
- We hypothesized that we could identify infants at risk for growth failure in the first few weeks of life based on their microbiome profile, leading to better outcomes.
- To identify age and growth discriminatory taxa, we developed machine learning models for age prediction based on microbiome profiles as well as classification for normal growth or growth failure.

## Analysis Plan

- **Random Forest Regression:** Age predictions were generated for infants using microbiome profiles followed by calculation of microbiota for age Z-score (MAZ) and relative microbiota maturity (RMM). These were compared between healthy infants and those with growth failure (2).
- **Random Forest Classification:** We used microbial profiles with additional metadata features to predict growth outcomes using a 10-fold cross-validation and feature step-down approach.
- **Alpha diversity:** SplinectomeR (5) was used to calculate differences in microbial richness between normal growth and growth failure infants over time.
- **Differential Taxa:** MetaLonDA (6) was used to assess the difference in absolute abundance of taxa between normal growth and growth failure over time.

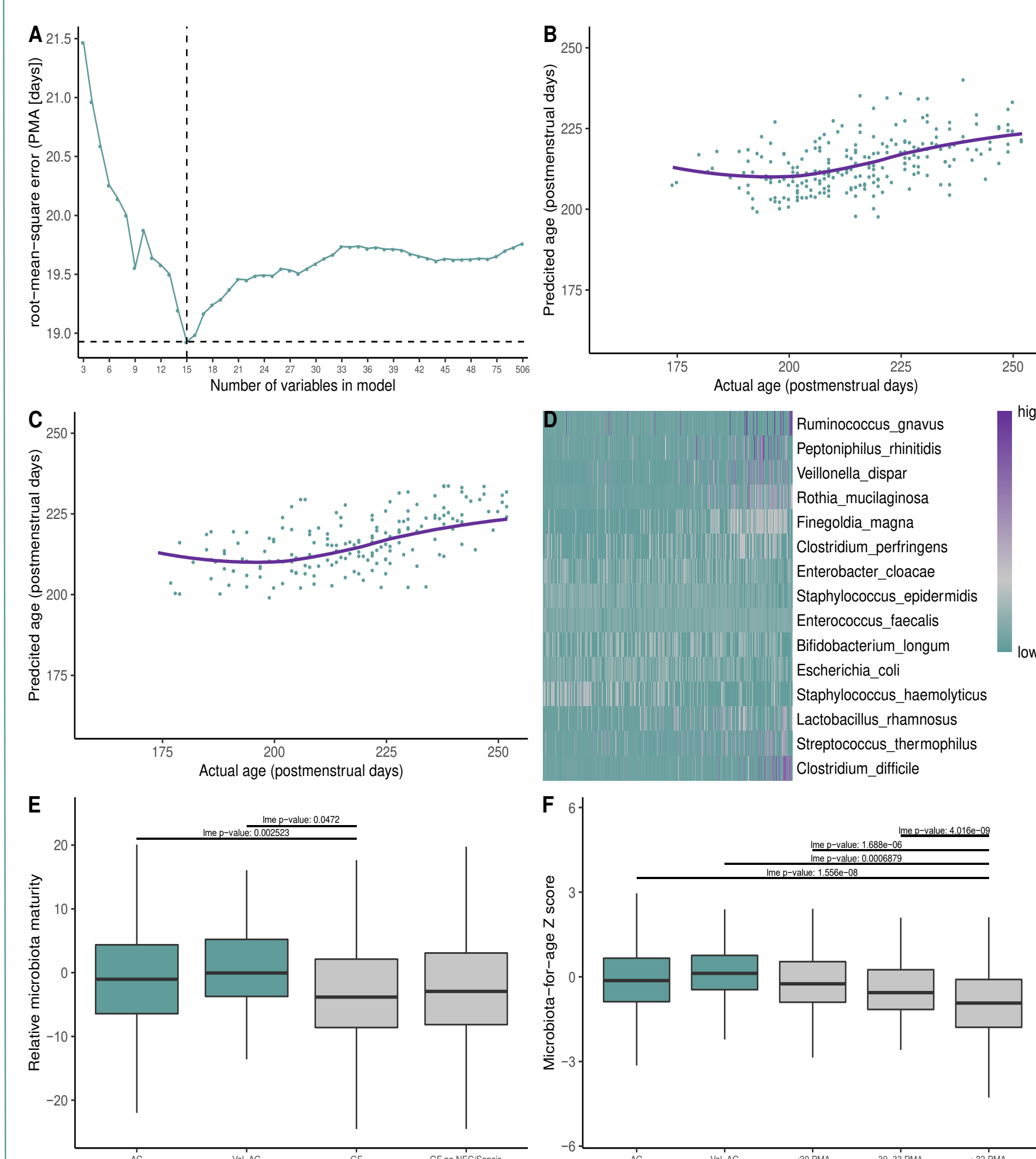
## Study Design

- **Study Population:** 267 preterm infants from 3 different clinical sites from birth to hospital discharge.
- **Sample collection:** Stool samples (n=2996) were collected longitudinally from 1 to 174 days of life, from infants with normal growth (n= 157), growth failure (n=102) and infants that died (n=8). Growth Failure is defined as birth-to-discharge weight z-score decline of  $\geq 1.2$ .
- **Sample Processing:** Extracted DNA was sequenced via shotgun metagenomic sequencing at a mean depth of 28,390,685 sequences.
- **Data Generation:** Shotgun sequencing was annotated using MetaPhlan2 and HUMAnN2 (3, 4).
- **Covariates:** Growth Status, Clinical Sites, Probiotic (Yes/No), Sepsis, Necrotizing Enterocolitis, Mode of Birth, Gender, Gestational Age at Birth, Post-Menstrual Age.

## Results

### Random forest regression revealed differences in microbiota age between healthy and growth failure infants

- A stepdown approach that systematically reduces model complexity and improves performance, finds a minimal model with the best performance to include 15 features with an average error of  $\pm 19$  days postmenstrual age.
- Models consistently predict higher ages for young infants and lower ages for old infants.
- Several taxa in the model show clear abundance patterns over infant's age. Some show higher relative abundance in older infants (e.g. *Finegoldia magna* and *Peptoniphilus rhinitidis*), while others show the opposite pattern (e.g. *Staphylococcus haemolyticus*).
- Growth failure infants have reduced relative microbiota maturity and microbiota-for-age Z scores relative to healthy infants.



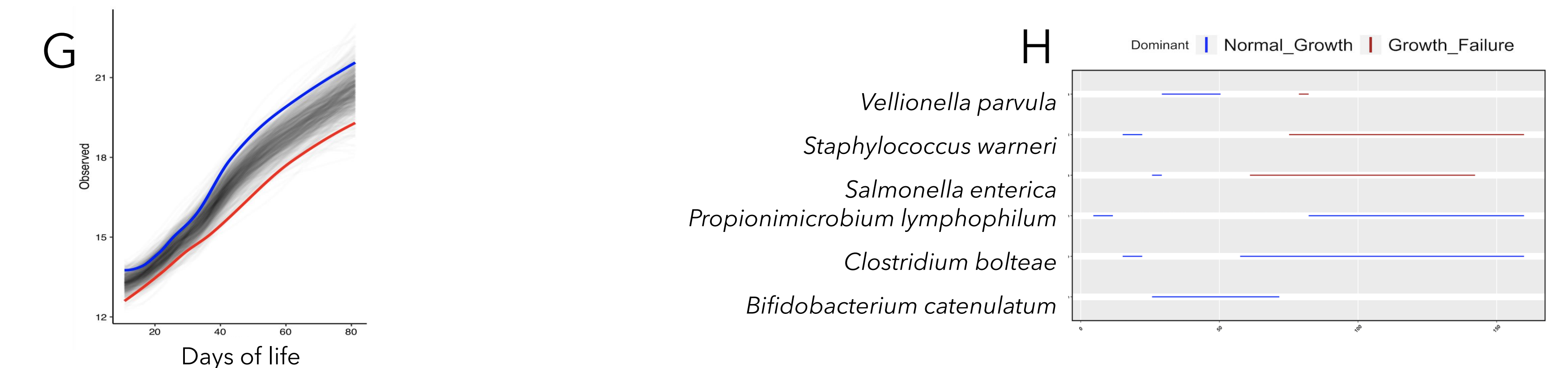
**Figure 1 (Left): Random forest regression using microbiome profiles of healthy infants for model generation.** For all plots, healthy infants are in green and infants with growth failure are in gray. (A) Model performance (error rate) using a step-down approach for feature selection. (B-C) Actual age vs Predicted age for the model training set alone (25 infants, B), and the test set alone (17 infants, C). (D) Heatmap of the 15 taxa that were included in the final model. Only samples from healthy infants are shown and samples are ordered from left to right in increasing age of the infant from which the sample was taken. Colors indicate row-normalized abundance. (E) Relative microbiota maturity (RMM) for various subsets of infants (AG: appropriate growth, Val\_AG: validation set of appropriate growth, GF: growth failure, GF no NEC/Sepsis: growth failure with no NEC or sepsis). (F) Microbiota for age Z-score (MAZ) for appropriate growth infants and several age subdivisions of growth failure infants.

### Random forest classification revealed taxa discriminatory for growth status and differences in classification accuracy over time

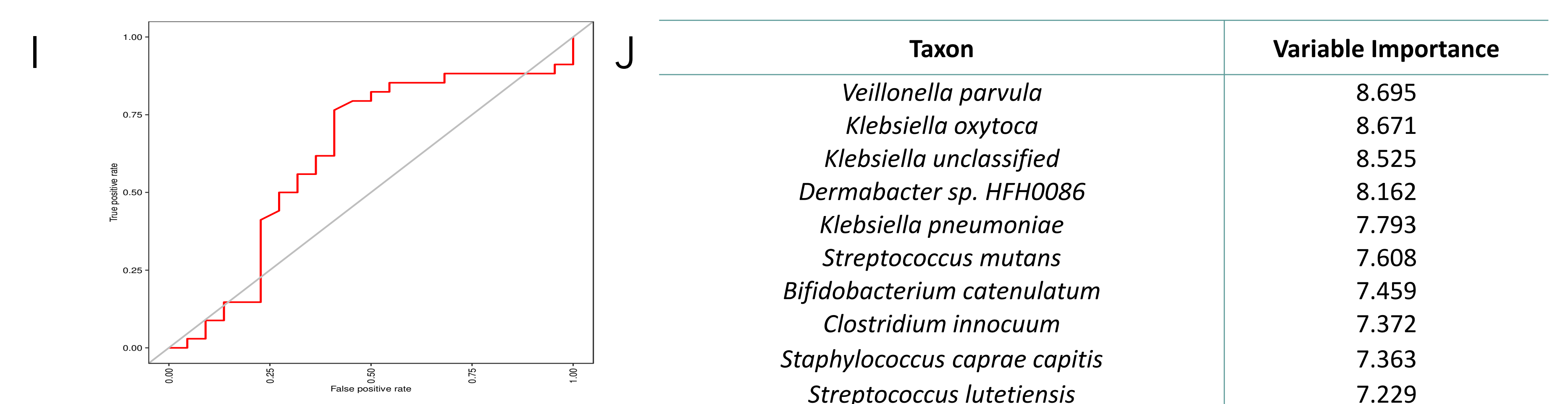
- Using a feature stepdown approach with samples subset to different DOL time windows, the best-performing model is for the 'Samples  $\leq 15$  DOL' time window for a reduced set of 10 features, with an average AUC-ROC value of 0.81.
- The best-performing model predicts growth status at 70% overall accuracy, with notably better performance when predicting Normal Growth compared to Growth Failure.

### Normal and growth failure infants have differing richness and composition

- Normal growth infants have significantly higher microbial richness ( $p < 0.05$  from day 30 to day 55) compared to those with growth failure status.
- *Vellionella parvula* & *Bifidobacterium catenulatum* were identified as differentially abundant taxa among normal growth infants.



**Figure 2 (Above): Differences in alpha and beta diversity and taxa over time.** (G) Microbial richness by growth status with respect to time. The shaded area represents the 95% confidence interval for no difference between two groups. (H) Microbial taxa differentially abundant by growth status with respect to time, by FDR corrected p value  $< 0.05$ .



**Figure 3 (Above): Random forest classification of growth status using microbiome profiles.** (I) AUC-ROC plot for the best-performing step of the feature stepdown for the Samples DOL  $\leq 15$  DOL model against the Test Set samples. (J) Taxa by descending feature importance from the best-performing step of the feature stepdown for the Samples DOL  $\leq 15$  DOL model.

## Conclusions

- Growth failure infants showed lower microbial richness and altered microbial composition compared to normal growth infants.
- Random Forest Regression identified 15 taxa that were most important for age prediction, resulting in a final model explaining 79% of the variance.
- Random Forest Classification predicted overall growth status with 70% accuracy, with 10 taxa found to be most important in growth status prediction in the Samples  $\leq 15$  DOL model.

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