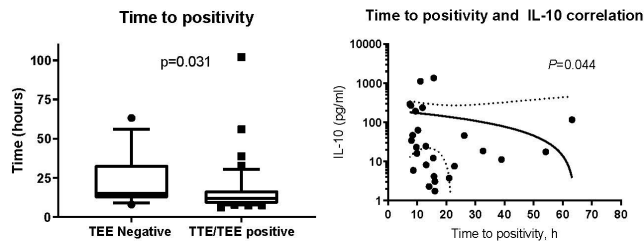


demographic and infection characteristics were collected. A 10-multiplex TH1/TH2 cytokine analysis was performed using electrochemoluminescence with the Meso-Scale Discovery platform analyzed by Mann-Whitney U.

Results. Patients' median values were significantly elevated and above the normal range in CF for IL-1 β ($P = 0.029$), IL-10 ($P = 0.018$), TNF- α ($P = 0.042$), and IL-6 ($P = 0.006$) (figure). Epidural abscess source was associated with CF, but no other host or pathogen characteristics correlated to outcome. Patients infected with isolates with VAN MIC = 2 mg/L (by Etest and broth dilution) had lower concentrations of IL-1 β and IL-10 ($P = 1.5$ mg/L. In ROC analysis, IL-1 β , IL-10, TNF, and IL-6 were higher sensitivity and specificity predictors of CF (AUC 0.65–0.71; $P = 0.05$).

Conclusion. A suboptimal host immune response to SAB at presentation predicts adverse clinical outcomes. IL-10, TNF- α , and IL-6 serum concentrations appear to reflect immunopathology in patients with SAB. These predictive markers may be considered in therapeutic clinical decision-making, such as escalation of alternative therapies in high-risk patients and/or de-escalation treatment in low-risk patients. These data offer steps toward further refining therapeutic precision for patients with SAB beyond the standard clinical or microbiologic metrics that are employed in current practice.



Disclosures. All authors: No reported disclosures.

413. Differences in Inflammatory Mechanisms in *Pseudomonas aeruginosa* and *Staphylococcus aureus* Infections in Cystic Fibrosis

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Session: 49. Inflammation and Infectious Diseases

Thursday, October 3, 2019: 12:15 PM

Background. Chronic bacterial lung infections are the primary cause of morbidity and mortality in cystic fibrosis (CF). The most common CF pathogens, *Pseudomonas aeruginosa* (*P. aeruginosa*) or *Staphylococcus aureus* (*S. aureus*), are common commensal or environmental organisms that adapt to the CF lung. We sought to investigate whether adaptation from early lung colonizer to chronic pathogen alters the bacterial effects on host inflammation.

Methods. *P. aeruginosa* ($n = 25$) and *S. aureus* ($n = 25$) isolates from CF patients with early and chronic infections were acquired from Seattle Children's CF. Environmental ($n = 8$) and clinical, non-CF *P. aeruginosa* ($n = 8$) isolates were obtained from the University of Ottawa. *P. aeruginosa* reference strain PA14 and PA14 transposon mutants for T3SS and flagellin were used to observe the relationship between cell death and cytokine production. We infected THP-1-derived macrophages (PMA differentiated) *in vitro* for 3 hours with various MOIs. We subsequently measured cell death of THP-1-derived macrophages using neutral red assay and cytokine production using ELISAs.

Results. Infections with PA14 mutants and non-CF *P. aeruginosa* isolates demonstrated that rapid cell death of THP-1-derived macrophages caused a reduction in cytokine production relative to strains that did not cause as much cell death. At 10 MOI, early *P. aeruginosa* isolates from CF patients induced more THP-1-derived macrophage cell death compared with chronic isolates ($P < 0.0001$). Chronic *P. aeruginosa* isolates induced greater production of TNF, IL-8, and IL-6 ($P < 0.01$, $P < 0.0001$, and $P < 0.0001$, respectively) compared with early strains. No difference in IL-1 β production was observed. When controlling for cell death between the two groups by using heat-killed bacteria, the only difference maintained was in TNF production ($P < 0.01$). Between early and chronic *S. aureus* isolates, the one difference observed was greater IL-8 production among early isolates ($P < 0.01$).

Conclusion. Chronic *P. aeruginosa* isolates from CF patients induce less cell death but more TNF, IL-8, and IL-6 production compared with early isolates. This suggests that *P. aeruginosa* producing chronic infections induce inflammatory signals that may contribute to increased morbidity among CF patients.

Disclosures. All authors: No reported disclosures.

414. Developing Digital Phenotypes of Primary Immune Deficiencies Using Machine Learning on a Large Electronic Health Record Database

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Background. More than 350 genetic disorders cause immune deficiencies; given the rarity of these conditions, in-depth study of infections associated with primary immune deficiencies (PID) requires extremely large sample sizes from broad populations. Using a large electronic health record (EHR) dataset, we linked clinical and microbiologic data to develop digital phenotypes for PID.

Methods. Using the Cerner HealthFacts EHR dataset from 2009 to 2017 we extracted clinical and microbiologic data for hospitalizations from patients <18 years old with ICD9/10 PID diagnoses and ≥ 1 positive culture for infection. Machine learning models were used to identify key features to predict PID diagnosis. Features included patient and hospitalization characteristics; infectious agent and infection site; and selected comorbidities. Model validation was done using the area under the receiver operating characteristic (AUC) curve.

Results. Overall 1316 patients with a PID were identified (Table 1). The 10 most common pathogens identified by PID are listed in Table 2. The models classified DiGeorge syndrome (positive predictive value 49%), functional disorders of polymorphonuclear neutrophils (PMN) (PPV 43%), and common variable immunodeficiency (CVID) (PPV 47%) better than combined immunodeficiency (CID) (PPV 20%); the overall true positive rate was 47% with an AUC of 0.73. Predictive features for each PID were as follows: CVID—having enteritis, hypertension, and pneumonia (Figure 1a); PMN—having hypoxia and hypertension (Figure 1b); DiGeorge syndrome—having congenital deformities and not having hypertension (Figure 1c); CID—finding *Staphylococcus aureus* in a wound or *Escherichia coli* in the blood were predictive of CID (Figure 1d).

Conclusion. Early models demonstrate some discrimination, specifically for more common PIDs (CVID) and those with highly identifying factors (DiGeorge syndrome). These models can be improved by including a wider array of clinical data, and they provide a first look at a new methodology to digitally phenotype PIDs for future diagnostic use.

Table 1. Patient counts by PID diagnoses

PID Diagnoses	Number of Patients	Percentage of Patients
Common Variable Immunodeficiency	485	36.9%
DiGeorge Syndrome	442	33.6%
Functional Disorders of Polymorphonuclear Neutrophils	207	15.7%
Combined Immunodeficiency - Unspecified	182	13.8%
Total	1316	100%

Table 2. Ten most frequent infections per PID diagnosis

Diagnosis Description	Isolate Name	Infection Site	Infection Count	Infection %
Common variable immunodeficiency	<i>Pseudomonas aeruginosa</i>	Respiratory	315	10.9%
	<i>Candida albicans</i>	Respiratory	248	7.9%
	<i>Staphylococcus aureus</i>	Respiratory	155	4.9%
	<i>Staphylococcus aureus</i>	Wound	105	3.3%
	<i>Staphylococcus aureus</i> Methicillin Resistant	Respiratory	103	3.3%
	<i>Streptococcus pneumoniae</i>	Respiratory	85	2.7%
	<i>Haemophilus influenzae</i>	Respiratory	79	2.5%
	<i>Stenotrophomonas maltophilia</i>	Respiratory	77	2.4%
	<i>Candida glabrata</i>	Respiratory	56	1.8%
	<i>Serratia marcescens</i>	Respiratory	54	1.7%
Total			1277	48.60%
DiGeorge Syndrome	<i>Pseudomonas aeruginosa</i>	Respiratory	148	12.2%
	<i>Staphylococcus aureus</i>	Respiratory	54	4.5%
	<i>Stenotrophomonas maltophilia</i>	Respiratory	48	4.0%
	<i>Monocilia catarrhalis</i>	Respiratory	43	3.6%
	<i>Serratia marcescens</i>	Respiratory	31	2.6%
	<i>Staphylococcus epidermidis</i>	Blood	29	2.4%
	<i>Coliforms</i>	Respiratory	28	2.3%
	<i>Klebsiella pneumoniae</i>	Respiratory	28	2.3%
	<i>Staphylococcus aureus</i> Methicillin Resistant	Respiratory	28	2.3%
	<i>Enterobacter cloacae</i>	Respiratory	26	2.1%
Total			463	38.3%
Functional disorders of polymorphonuclear neutrophils	<i>Pseudomonas aeruginosa</i>	Respiratory	52	5.5%
	<i>Candida albicans</i>	Respiratory	49	5.2%
	<i>Staphylococcus aureus</i>	Wound	30	3.2%
	<i>Staphylococcus aureus</i>	Respiratory	28	3.0%
	<i>Staphylococcus aureus</i> Methicillin Resistant	Miscellaneous	28	3.0%
	<i>Staphylococcus aureus</i> Methicillin Resistant	Respiratory	23	2.4%
	<i>Staphylococcus aureus</i>	Miscellaneous	22	2.3%
	<i>Stenotrophomonas maltophilia</i>	Respiratory	18	1.9%
	<i>Mycobacterium avium-intracellulare</i> complex	Respiratory	17	1.8%
	<i>Staphylococcus aureus</i> Methicillin Resistant	Wound	16	1.7%
Total			283	30.1%
Combined immunodeficiency, unspecified	<i>Staphylococcus aureus</i>	Wound	41	5.0%
	<i>Pseudomonas aeruginosa</i>	Respiratory	33	4.0%
	<i>Staphylococcus aureus</i>	Respiratory	30	3.6%
	<i>Staphylococcus aureus</i>	Blood	25	3.0%
	<i>Candida albicans</i>	Respiratory	21	2.6%
	<i>Escherichia coli</i>	Blood	21	2.6%
	<i>Staphylococcus aureus</i> Methicillin Resistant	Wound	17	2.1%
	<i>Escherichia coli</i>	Gastrointestinal	15	1.8%
	<i>Staphylococcus aureus</i> Methicillin Resistant	Respiratory	15	1.8%
	<i>Stenotrophomonas maltophilia</i>	Respiratory	15	1.8%
Total			233	28.3%

The most common infection/site pairs for each of the PIDs in the model. The percentage of infections is out of the total per PID.

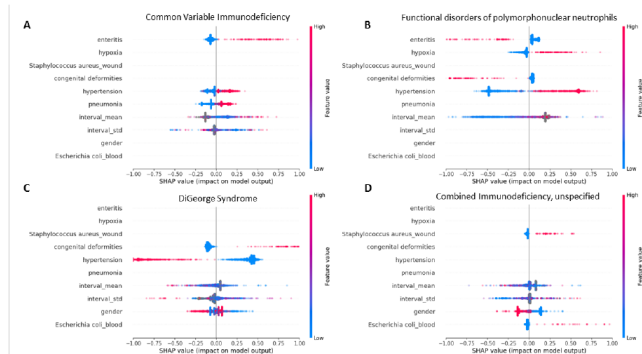


Figure 1. Five most important features per PID for the model's classification. Gradient Boosted Machine was used to classify primary immune deficiencies using a variety of clinical features. Each dot represents one patient. Red dots indicate presence of feature (binary variables= "ever had" or "female"), continuous variables= "high"), blue dots indicate absence of feature (binary variables= "never had" or "male"), continuous variables= "low"). The "interval" features refer to the time between microbiology tests. Positive SHAP (SHapley Additive exPlanations) values indicate the feature was predictive of being in the cluster (i.e. having that PID). Negative SHAP values indicate the feature was predictive of not being in the cluster.

Disclosures. All authors: No reported disclosures.