## **A Diagnostic Classifier for Pediatric Chronic Graft-Versus-Host Disease: Results of the ABLE /**

## **PBMTC 1202 Study**

### **SUPPLEMENTARY DATA FILES**

Geoffrey D.E. Cuvelier, MD; Bernard Ng, PhD; Sayeh Abdossamadi, PhD; Eneida R. Nemecek, MD, MS; Alexis Melton, MD; Carrie L. Kitko, MD; Victor A. Lewis, MD; Tal Schechter, MD; David A. Jacobsohn, MD; Andrew C. Harris, MD; Michael A. Pulsipher, MD; Henrique Bittencourt, MD, PhD; Sung Won Choi, MD; Emi H. Caywood, MD; Kimberly A. Kasow, DO; Monica Bhatia, MD; Benjamin R. Oshrine, MD; Sonali Chaudhury, MD; Donald Coulter, MD; Joseph H. Chewning, MD; Michael Joyce, MD, PhD; Süreyya Savaşan, MD; Anna B. Pawlowska, MD; Gail C. Megason, MD; David Mitchell, MD; Alexandra C. Cheerva, MD; Anita Lawitschka, MD; Elena Ostroumov, PhD; and Kirk R. Schultz, MD.



**Supplementary Table 1**. Baseline characteristics. ALL, Acute Lymphoblastic Leukemia; AML, Acute Myelogenous Leukemia; HLA, Human Leukocyte Antigen; MDS, Myelodysplastic Syndrome



# **I. Flow Cytometry / Phenotyping Methods and Cellular Populations**

Blood was drawn from the study participant and shipped overnight to arrive in the Schultz laboratory the following day. Phenotyping was usually performed on the day of sample arrival in the Schultz laboratory, and always within 5-days. Six flow cytometry panels were designed to evaluate for various subpopulations of T, TREGS, B, NK cells, and myeloid cells. All antibodies, corresponding conjugated dyes, and vendors are provided here:



### **Supplementary Table 2. Flow cytometry antibodies used per panel**



Samples were stained in the dark for 12 minutes at room temperature followed by treatment with fix/red blood cell lyze solution (eBiosceinces, Thermo Fisher Scientific, Waltham, MA). For intracellular staining, cells were made permeable using BD Perm II solution (BD Biosciences Mississauga, ON, Canada). Flow cytometry data were acquired using BD LSR Fortessa X-20 Special Order four channel flow cytometer (BD Biosciences, San Jose, CA). A minimum of 300,000 events were acquired for all panels. Instrument settings was also standardized using SPHERO Rainbow Calibration particles 6 peaks (Sphereotech, Lake Forest, IL) to adjust laser power drifts over time. Flow cytometry analysis files were analyzed using Kaluza software v2 (Beckman Coulter, Mississauga, ON, Canada). Flow cytometry accuracy and reproducibility were ensured by the approaches described in detail in the supplement of Schultz et al. Blood 2020: 135(15): 1287- 1298 (reference 17 in manuscript) with minimal batch variability.

Cellular subpopulations were defined as follows (adapted from Schultz et al. Blood 2020: 135(15): 1287-1298):

### **Supplementary Table 3: Immunophenotype and Cell Type Subpopulation**







### **II. Development of Machine Learning-Based Classifier for Chronic GVHD Diagnosis**

 In addition to analyzing each marker in a univariate manner, we developed a machine learning-based classifier that combines multiple cellular and plasma markers along with clinical factors for diagnosing whether a patient has cGVHD. The approach is summarized in Figure 4 of the manuscript. We first randomly selected 10 cGVHD samples and 10 control samples as the test set for classifier evaluation. If a control sample was from one of the selected cGVHD subjects (i.e., a measurement made prior to cGvHD onset) or another sample had already been drawn from the same control subject, we randomly drew another control sample, since in real clinical settings, we would immediately diagnose a subject when marker measurements become available. All remaining samples, except those acquired at later time points from subjects in the test set, were used for classifier training. To account for outlier marker values, we performed winsorization by first estimating the median and median absolute deviation (MAD) of each marker based on the training samples. We then clipped all marker values at 3 standard deviations away from the training median with standard deviation estimated as  $1.483 \cdot \text{MAD}.$ <sup>1</sup> To deal with missing marker values in the training set, we applied k-nearest neighbors (k=15) to impute the

missing values. To reduce the number of markers, we performed feature selection using a bootstrapping approach. Specifically, we extracted 1,000 bootstrap samples from the training set. For each bootstrap sample, we applied a Student's t-test to compare the marker values of cGVHD samples against controls for each marker. Markers with p<0.05 for >99% of the bootstrap samples (i.e., selection frequency >0.99) were selected for classifier training. We trained a support vector machine (SVM) classifier with the selected markers and all clinical factors used in the regression analysis. SVM finds an optimal weighting of the selected markers and clinical factors that best separates cGVHD samples from control samples. To account for class imbalance (i.e., the training set had many more control samples than cGVHD samples), we set the penalty weight for misclassifying cGvHD (controls) to the number of training samples over the number of cGvHD (control) samples. Setting a higher penalty for misclassifying cGVHD reduces the bias towards classifying samples as controls. To deal with missing marker values in the test set, we applied k-nearest neighbors (k=15) using only values of the selected markers from training samples to impute the missing values in each test sample. Imputing each test sample separately without using other test samples better emulates real clinical settings. To evaluate the classifier, we applied it to the test set and computed its positive predictive value (PPV), negative predictive value (NPV), and area under the receiver operator characteristic curve (AUC). PPV is the proportion of test samples classified as cGvHD that are truly cGvHD, and NPV is the proportion of test samples classified as controls that are truly controls. The described procedures were repeated 1,000 times with different random train-test sample splits to assess variability in classification performance arising from sample variability. The average training AUC over the 1,000 random train-test sample splits was 0.95 ( $\pm$  0.01). We note that the selected markers would

normally vary across random train-test sample splits due to sample variability. However, since we used a bootstrapping procedure with an extremely high selection frequency threshold of 99%, the selected markers highly overlapped across the random train-test sample splits. To report one representative set of markers for future validation, two common strategies are often taken in practice. One strategy is to report markers that are selected in majority (e.g. 99%) of the random train-test sample splits. The other strategy is to apply the marker selection procedure to all samples. Since we used bootstrapping with a selection frequency threshold of 99% as our marker selection procedure, the selected markers were identical with both strategies. The reported selection frequencies correspond to applying our marker selection procedure to all samples.

#### **Reference:**

1. I. Gijbels, M. Hubert: Robust and Nonparametric Statistical Methods, in Brown SD, Tauler R, and Walczak B (eds): Comprehensive Chemometrics. Chemical and Biochemical Data Analysis. Elseiver, 2009, volume 1, pp 189-211.

**Supplementary Table 4.** *Mixed effect modeling of* **cellular and plasma chronic GVHD diagnostic biomarkers (present at the onset of chronic GVHD) compared to control individuals without chronic GVHD.** Chronic GVHD patients included all chronic GVHD severities (mild, moderate, severe) according to the NIH consensus criteria. Biomarkers highlighted in blue also met the same criteria at all three time points in the fixed effect model. Biomarkers highlighted in yellow met the same criteria in one or two time points (but not all three time points) in the fixed effect model . AUC, Area Under Curve; NKREG, Regulatory NK cell; RTE, Recent Thymic Emigrant (CD4+CD45RA+CD31+); Th, Helper T cell (CD4+); TREG, Regulatory T cell (CD4+CD127<sup>Low</sup>CD25+).





**Supplementary Table 5.** *Mixed effect modeling of* **cellular and plasma chronic GVHD diagnostic biomarkers (present at the onset of chronic GVHD) in moderate-severe chronic NIH consensus criteria GVHD (n=34) compared to control individuals without chronic GVHD.** Patients with mild chronic GVHD according to the NIH consensus criteria were removed from analysis. AUC, Area Under Curve; NKREG, Regulatory NK cell; RTE, Recent Thymic Emigrants (CD4+CD45RA+CD31+); Th, Helper T cell (CD4<sup>+</sup>); T<sub>REG</sub>, Regulatory T cell (CD4<sup>+</sup>CD127<sup>Low</sup>CD25<sup>+</sup>).





**Supplementary Table 6.** *Fixed effect modeling of* **cellular and plasma chronic GVHD diagnostic biomarkers (present at the onset of chronic GVHD) compared to all control individuals without chronic GVHD.** Chronic GVHD patients included all chronic GVHD severities (mild, moderate, severe), according to the NIH consensus criteria. Markers highlighted in blue met these three criteria at all three time points of chronic GVHD onset (early-, mid-, and late-onset). Markers highlighted in yellow met the three criteria at one or two (but not all three) time points for chronic GVHD onset. AUC, Area Under Curve; NKREG, Regulatory NK cell; RTE, Recent Thymic Emigrants (CD4<sup>+</sup>CD45RA<sup>+</sup>CD31<sup>+</sup>); Th, Helper T cell (CD4<sup>+</sup>); T<sub>REG</sub>, Regulatory T cell (CD4<sup>+</sup>CD127<sup>Low</sup>CD25<sup>+</sup>).





**Supplementary Table 7. Classifier weights of various cellular, plasma, and clinical factors used in the diagnostic classifier.**



**Supplementary Table 8. Exploratory** *Mixed effect modeling of* **cellular and plasma chronic GVHD diagnostic biomarkers (present at the onset of chronic GVHD) by type of chronic GVHD compared to all control individuals without chronic GVHD.** All three criteria to be a biologically relevant potential diagnostic biomarker had to be met, including: (1) an effect ratio ≥ 1.3 or ≤0.75, meaning the mean percentage in the chronic GVHD group had to either 30% greater or 30% lower  $(1.0 / 1.3 = 50.75)$  compared to the mean value of the control group; (2) the area under the curve (AUC) on the receiver operator curve had to be ≥0.60; and (3) p <0.05. None of the markers met the p-value criteria for Bonferroni correction. AUC, Area Under Curve; NKREG, Regulatory NK cell; RTE, Recent Thymic Emigrants (CD4<sup>+</sup>CD45RA<sup>+</sup>CD31<sup>+</sup>); Th, Helper T cell (CD4<sup>+</sup>); TREG, Regulatory T cell (CD4<sup>+</sup>CD127<sup>Low</sup>CD25<sup>+</sup>).







**Supplementary Figure 1. Failure cohort not captured by the classifier.** For different random train-test sample splits, different samples would be misclassified. We divided the samples based on the proportion of random splits for which they were misclassified, with 0.8 as the threshold to define the failure cohort. (A) The proportion of random splits misclassified for each sample is represented by a dot within the violin plots. The white circle is the median. A key observation (as would be expected) is that samples from cGvHD subjects prior to their onset of cGVHD (samples drawn at day 100 +/-14 days and 6-months +/- 1 month) were more often misclassified. (B) Peripheral blood stem cell grafts (PBSC) compared to non-PBSC grafts have a higher proportion of random splits misclassified. (C) The failure cohort (denoted as "1") is on average older.

.

**A**