Supporting Information

Rioux et al. 10.1073/pnas.0909307106

SI Text

Cohort Descriptions. The entire set of DNA samples consisted of 10,576 individuals derived from 13 cohorts, specifically from 7 different immune-mediated diseases and 3 shared control cohorts. The population from which each cohort was derived, as well as the distribution of DNAs for each disease, were as follows: 654 SLE cases from the United Kingdom, 486 SLE cases from the United States, 427 CD cases from the United States and Italy, 688 UC cases from Italy, 1,343 RA cases from Sweden, 674 RA cases from the United States, 453 MG cases from Sweden, 270 IGAD cases from Sweden, 502 MS mother-father-affected child trios from the United Kingdom, and 531 MS motherfather-affected child trios from the United States for a total of 3099 DNAs, 1,056 controls from the United States, 673 controls from Sweden, and 753 controls from the United Kingdom. Of the 1,343 Swedish RA cases, only 657 ACPA-positive individuals were used in the analysis. After quality control, there remained 643 SLE cases from the United Kingdom, 483 SLE cases from the United States, 396 CD cases from the United States and Italy, 667 UC cases from Italy, 1,308 RA cases from Sweden, 604 RA cases from the United States, 438 MG cases from Sweden, 267 IGAD cases from Sweden, 494 MS mother-father-affected child trios from the United Kingdom, and 518 MS motherfather-affected child trios from the United States for a total of 3,036 DNAs, 1,049 controls from the United States, 672 controls from Sweden, and 746 controls from the United Kingdom.

DNA Handling and SNP Genotyping. All DNAs were received at the Broad Institute Center for Genotyping and Analysis (CGA) in 96-well plates. The concentration of double-stranded DNA was assessed using PicoGreen (Molecular Probes), and concentrations were normalized to 50–100 ng/ μ L. Some samples were native DNA, and others underwent whole-genome amplification (WGA) before receipt. Native and WGA DNAs were never arrayed on the same plate for Illumina processing. Overall, 120 96-well plates were processed; of these, 17 contained WGA DNA. DNAs from HapMap CEU cell lines (Coriell Cell Repositories) served as process controls. We genotyped 96-well plates of DNA on the CGA's Illumina GoldenGate BeadLab platform as described previously.

Genotype calls were performed using the BeadStudio program (Illumina) to define genotype clusters based on signal intensity. The 103 native DNA plates and the 17 WGA DNA plates were clustered in a stepwise fashion, the rationale being that native DNA samples exhibit better defined and separated (tighter) clusters than WGA DNA. First, for all native DNA samples, the genotype cluster positions (centers and sizes) were determined automatically using the BeadStudio clustering algorithm, followed by manual review. During the manual review process, advanced user modifications were applied to reflect optimally the distribution of sample set genotypes for each SNP. These adjusted user calls received a second round of manual review. After the final clusters were defined for the native DNAs, the modified static cluster definitions (as an .egt file) were applied independently to the WGA DNA plate intensities. The manual review process of the WGA DNAs followed the same iterative workflow as the review of native DNAs; advanced user modifications were applied to reflect optimally the sample set per SNP. Certain SNP assays were marked as failed within BeadStudio because of either poor cluster separation or low signal intensity. The genotypes for the remaining, passing SNPs

were exported from BeadStudio and analyzed as described in the following sections.

HLA Typing. Previous 2- or 4-digit typing of *HLA-A*, *HLA-B*, *HLA-C*, *HLA-DRB1*, and *HLA-DQB1* was available for 15%, 18%, 9%, 24%, and 71% of the patient datasets, respectively. HLA typing was performed by different methodologies available to the investigators, including PCR-based sequence-specific oligonucleotide probe reverse-line blot assay, sequence-specific oligonucleotide (LABType) typing, and exons 2/3 sequencebased typing.

Imputation of Genotypes at HLA Genes. For individuals for whom classic HLA alleles were not available, HLA genotypes were imputed from SNPs in the MHC using a recently developed statistical approach (1). Briefly, this method utilizes a database of SNP genotypes and classic HLA alleles for chromosomes when the haplotype phase is known (or has been estimated) and uses a population genetic model to impute HLA alleles for additional individuals for whom only SNP data are available. The SNPs used for HLA allele imputation were selected from the intersection of the SNPs in the database and those genotyped on individuals in the present study. The training database used was from a previously created map of 7,500 SNPs, deletion insertion polymorphisms, and HLA alleles for 182 Utah residents (29 extended families containing 45 unrelated parent-offspring trios) of European ancestry in the Centre d''Etude du Polymorphisme Humain collection (2). We used a forward-selection, backwards-elimination approach to search the space of possible SNP sets efficiently. For each set of SNPs, leave-one-out crossvalidation was used to assess prediction accuracy in the training data, averaging across all chromosomes in the database. For each HLA locus the best set of up to 40 prediction SNPs was chosen to be used for imputation. SNPs chosen for predicting each allele are available on request.

To validate the imputed classic HLA type data used in our analyses, we compared our imputed data with available 4-digit classic HLA data. Specifically, we calculated the sensitivity, specificity, and positive predictive value of the imputed HLA data for the *HLA-B*, *HLA-C*, and *HLA-DRB1* loci in the CD dataset (450 samples with *HLA-B* and *HLA-C*), SLE dataset (313 samples with *HLA-DRB1*), and MS dataset (2,257 samples with *HLA-DRB1*), because these disease cohorts had with the most complete datasets for the classic typing. Results are shown in [Fig.](http://www.pnas.org/cgi/data/0909307106/DCSupplemental/Supplemental_PDF#nameddest=SF1) [S1.](http://www.pnas.org/cgi/data/0909307106/DCSupplemental/Supplemental_PDF#nameddest=SF1)

Discrepancies between imputed and typed classic HLA alleles could result from errors in the SNP typing, in the imputation process itself, or in the actual HLA typing. Although molecular HLA typing is considered the reference standard, its high cost often limits the number of loci typed, the level of resolution (2 digit vs. 4 digit), and the number of samples that can be typed in a given study. In addition, even in a single dataset, the classic HLA typing often is performed with a variety of laboratory methods and allele-calling algorithms. For example, the HLA typing in the IgAD cohort in the current dataset had been carried out over a period of 20 years using a variety of different methods (including serology and DNA-based typing). In this dataset there were discrepancies between the classic HLA and the imputed HLA genotypes in 94 individuals (64 *HLA-A*, 59 *HLA-B*, 55 *HLA-DRB1*, and 34 *HLA-DQB1* alleles). These samples therefore were retyped, using PCR sequence-specific primer (SSP) kits (Dynal Biotech). We then recalculated the sensitivity and

specificity of the imputed alleles against the typed alleles in both the original and the retyped data. When discrepancies were detected after retyping of the classic HLA loci, the sensitivity increased for many HLA alleles (e.g., from 72.7% to 90% for *HLA-A*11* and from 89.7% to 95.4% for *HLA-B*07*). The increased sensitivity observed in the retyped dataset showed that some original HLA genotypes were inaccurate and that some of the errors were actively corrected by the imputation algorithm. The final results showed an overall concordance of 95% between the SSP-based typing and the SNP-based imputation for most HLA alleles: close to 100% for the *HLA-A* alleles (with the exception of *HLA-A33* and *-A66*); 95% to 100% for most *HLA-B* alleles (notable exceptions being *HLA-B27*, *-B47*, and *-B55*); 90% to 100% for most *HLA-DR* alleles (exceptions being *HLA-DRB1***01* and *HLA-DRB1***09*); and 96% to 100% for the *HLA-DQ* alleles. For the noted exceptions, the imputation did not perform well because the training data did not contain samples (haplotypes) representing these alleles.

Statistical Analyses. We performed quality filtering of both samples and SNPs to ensure robust association testing. To determine the appropriate thresholds, we examined sample heterozygosity, Hardy-Weinberg equilibrium, Mendelian inheritance errors (ME), and inflation. We applied 5 filters iteratively: SNPs less than 70%, samples less than 90%, SNPs less than 95%, families with > 50 ME, and SNPs > 15 ME. After filtering, SNP and sample outliers disappear, and remaining samples and SNPs fall under normal distribution. Overall, 83.85% of the SNPs (1288/ 1536) and 97.48% of samples (10,309/10,576) passed quality control and were included in analysis; the average call rate after quality control was 99.0%.

Association testing of all SNPs and imputed HLA alleles was performed by the transmission disequilibrium test for the MS trios and by a standard χ^2 test carried out on a 2 \times 2 contingency table for case/control cohorts, as implemented in the PLINK analysis software (http://pngu.mgh.harvard.edu/purcell/plink/) (3). For case/control analyses, each disease cohort was paired with a matching population control cohort when available; otherwise, pairing was performed with the best-matching control cohort. Matching of the case/control cohorts was evaluated by calculating a genomic control coefficient (GCC) using the non-MHC SNPs that were included in the genotyping panel (see earlier sections). When more than a single-source population was available for a given disease, the case/control (e.g., the RA cohorts from the United States and Sweden) or trio cohorts (e.g., the MS cohorts from the United States and the United Kingdom) were combined into a single analysis cohort for increased power. Because an evaluation of the combined case/control cohorts by Cochran-Mantel-Haenszel analysis did not alter the association results significantly, all analyses were performed simply by combining cohorts. An overall GCC was calculated for each combined disease case/control population and was used to correct the association χ^2 results. Association results from the combined disease cohorts are reported as 2-tailed nominal significance p-values (GCC corrected for case-control cohorts).

Conditional logistic regression analyses were performed in the different disease cohorts for the top associated SNP and HLA alleles using the WHAP analysis software (http://pngu.mgh.harvard.edu/purcell/whap/). Briefly, each SNP and HLA allele was evaluated for independence from the top SNP or HLA allele in a pairwise fashion, and independent association signal results are reported as 2-tailed nominal significance p-values after GCC correction.

- 1. Leslie S, Donnelly P, McVean G (2008) A statistical method for predicting classical HLA alleles from SNP data. *Am J Hum Genet* 82:48–56.
- 2. de Bakker PI, et al. (2006) A high-resolution HLA and SNP haplotype map for disease association studies in the extended human MHC. *Nat Genet* 38:1166–1172.
- 3. Purell S, et al. (2007) PLINK: A toolset for whole-genome association and populationbased linkage analysis. *Am J Hum Genet* 81:559–575.

Fig. S1. Assessment of the quality of HLA allele imputation. Sensitivity, specificity, and positive predictive value were calculated for imputed HLA alleles in the datasets for which classic HLA typing data also were available (see *Materials and Methods*). These quality metrics are plotted as a function of allele frequencies in the extended HapMap CEU population (2). HLA alleles that are observed only once (or not at all) in the imputation training set were excluded.

S
A

Fig. S2. Results of association and logistic regression analysis for all 7 diseases. Results of allelic tests of association (*Top*) for SNPs*(black diamonds*) and imputed HLA alleles (*yellow boxes*). All association results are represented as the -log10 of the p-values (*y*-axis). The most highly associated SNPs and HLAs are highlighted in blue and red, respectively.

PNAS PNAS

The SNPs listed for each disease are part of the same equivalence class; they can explain the association observed for top association signal or can be said to be statistically equivalent to top signal. A SNP was defined as equivalent to the top signal if it showed a correlation of r2 $>$ 0.5 and caused the top signal to lose significance (p-value $>$ 0.05) following reciprocal conditional analysis.

Table S2. Full set of secondary signals

*Signal ID. Additional signals that show significant association to the trait following conditioning on primary signal and pairwise *r*² 0.5

Table S3. Summary of top primary and secondary associations

*Association signal reference numbers as described in Figure 2.

**The correlation neighborhood, as defined by the furthest markers showing the indicated correlation coefficients (0.8 or 0.5) or greater to the associated marker, were evaluated from the extended HapMap dataset described in Bakker et al. 2006.

***Size of region defined by the correlation neighborhood. ''-'' absence of correlated neighbor.

Letters on left side of table indicate shared signals.

Table S4. Performance of associated HLA alleles on validation datasets

Note:

PNAS PNAS

For each locus the type of association is indicated (see legend below). The number of individuals that carry the allele in the training data is shown, and the performance of the method on the various training datasets available is shown.

Legend:

xxx Top Association in Screening and Replication Datasets (Table 1).

xx Top Disease Specific Association Signals for the MHC in Entire Datasets (Table 2).

x Most Significant Secondary Association (Table 3).

s2 Variants that are statistically equivalent to primary association signal (Supporting Table 1).

s3 Appears in Full Set of Secondary Signals (Supporting Table 1).