Germline polymorphisms in the immunoglobulin kappa and lambda loci explain variation in the expressed light chain antibody repertoire

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Abstract

Variation in antibody (Ab) responses contributes to variable disease outcomes and therapeutic responsiveness, the determinants of which are incompletely understood. This study demonstrates that polymorphisms in immunoglobulin (IG) light chain loci dictate the composition of the Ab repertoire, establishing fundamental baseline differences that preclude functional Ab-mediated responses. Using long-read genomic sequencing of the IG kappa (IGK) and IG lambda (IGL) loci, we comprehensively resolved genetic variation, including novel structural variants, single nucleotide variants, and gene alleles. By integrating these genetic data with Ab repertoire profiling, we found that all forms of IG germline variation contributed to inter-individual gene usage differences for >70% of light chain genes in the repertoire, directly impacting the amino acids of expressed light chain transcripts, including complementarity determining region domains. The genomic locations of usage-associated variants in both intergenic and coding regions indicated that IG polymorphisms modulate gene usage via diverse mechanisms, likely including the modulation of V(D)J recombination, heavy and light chain pairing biases, and transcription/translation. Finally, relative to IGL, IGK was characterized by more extensive linkage disequilibrium and genetic co-regulation of gene usage, illuminating differential regulatory and evolutionary features between the two light chain loci. These results firmly establish the critical contribution of IG light chain polymorphism in Ab repertoire diversity, with important implications for investigating Ab responses in health and disease.

Main

Antibodies (Abs) are critical components of the adaptive immune system and are one of the most diverse protein families in the human body. The circulating Ab repertoire comprises hundreds of millions of unique antibodies [1,2], and its composition varies significantly between individuals [1–3]. The variability likely contributes to the diverse Ab responses observed across clinical settings, including infection [4–8], autoimmunity [9], and cancer [10]. Identifying the factors that contribute to variation in B cell-mediated immunity will inform disease diagnosis and treatment.

Human Abs are composed of two pairs of identical 'heavy' chains and 'light' kappa or lambda chains, encoded by genes located at three primary loci in the genome: the immunoglobulin (IG) heavy chain locus (IGH; 14q32.33), and the IG lambda (IGL; 22q11.2) and kappa (IGK; 2p11.2) loci [11]. Across the IG loci, there are >240 phylogenetically related functional/open reading frame variable (V), diversity (D) (specific to IGH), and joining (J) genes [12–15]. Selection of individual IG heavy and light chain genes during V(D)J recombination is a foundational step in the process of Ab generation. Increasing evidence indicates that genetic variation within the IG loci modulates the generation of the formation of the human Ab repertoire, contributing to the observed receptor diversity seen between individuals. This was initially supported in twin studies, which demonstrated that both naïve and antigen-stimulated Ab repertoires possess heritable characteristics [16–18]. Additionally, non-coding and coding IG heavy chain [12,19–26] and light chain [20,27–29] germline variants have been shown to affect Ab gene usage and antigen specificity.

Utilizing matched adaptive immune receptor repertoire (AIRR)-seq and comprehensive long-read sequencing genotyping of IGH in a cohort of 154 individuals, we recently demonstrated that approximately half of common germline variants in IGH were associated with variation in usage frequencies of the majority of IGHV, IGHD, and IGHJ genes within the IgM (naïve-enriched) repertoire [12]. Subsequently we showed that these genetic variants contribute to repertoire variation in early B cell developmental stages in the bone marrow, indicating direct impacts on V(D)J recombination [30]. This has raised the prospect that variants within the IGK and IGL loci exert similar effects on the formation of the light chain repertoire, and will associate with inter-individual Ab variation in the periphery. The heavy and light chains of an Ab must be paired and compatible to achieve specificity and functionality, and both heavy and light chains contribute to antigen binding. The identification and characterization of antigen-specific and disease-associated Abs requires comprehensive models of naïve and antigen-experienced repertoires, for which a detailed understanding of genetic variation in all three loci is essential. To this end, it is critical to recognize that IG loci are enriched with structural variants (SVs), including segmental duplications and inversions, limiting the utility of short-read sequencing to characterize genetic variation [12–15,31–34]. We previously demonstrated that long-read sequencing of diverse IGH [12,13,33], IGL [14], and IGK [15] haplotypes identifies genetic variation not recorded in reference databases, including catalogues of single-nucleotide variants and gene alleles.

Here, we pair long-read genomic sequencing of IGK and IGL with AIRR-seq at population-scale to identify *cis*-acting variants that explain inter-individual variation in light chain Ab repertoire features. We find

that genetic variants in IGK and IGL associate with gene usage frequency for the majority of light chain V and J

genes. These associations between germline polymorphism and gene usage persisted even in antigen-

experienced Ab repertoires. Analysis of lead variants revealed mechanisms by which genetic sequence can

impact gene usage frequencies, including missense and nonsense substitutions, as well as substitutions in

regulatory elements, such as recombination signal sequences. We find distinct structures of linkage

disequilibrium (LD) in IGK and IGL, with relatively high LD in IGK associating with coordinated usage of multi-

gene clusters. Finally, we demonstrate that genetic effects on gene usage contribute to amino acid variation in

V genes, as well as physicochemical properties of the CDR3, linking germline variations with Ab features that

contribute to antigen binding.

Results

Long-read genomic sequencing and genotyping of IGK and IGL loci and expressed light chain

antibody repertoire sequencing

We combined targeted long-read sequencing of IGK and IGL loci in 177 healthy individuals with newly

and previously [12] generated AIRR-seq for nearly all donors in the cohort (IGK, n=173, IGL, n=171). Donors

ranged in age from 18 to 57 years (mean: 32.3), representing both biological sexes (male, n=90; female,

n=87), and diverse genetic ancestry groups (**Supplementary Table S1**). Using our previously published

method [13], we performed targeted long-read single molecule real-time (SMRT) sequencing of the IGK proximal

and distal regions [15], and the IGL locus [14] (see **Supplementary Material**). From these data, we generated

sample-level variant callsets (SNVs and SVs), and IGK/L gene and allele germline sets, representing the most

comprehensive collection of such data types collected to date (see **Supplementary Material**). Importantly, this

dataset allowed for the identification of >300 novel germline IG alleles, as well as novel SNVs and SVs

(**Supplementary Fig. 2**).

To profile expressed IGK and IGL transcripts, AIRR-seq data was generated using 5' rapid amplification

of complementary DNA ends (5' RACE) on total RNA isolated from PBMCs collected from 173 individuals.

With germline IGKV, IGKJ, IGLV, and IGLJ alleles for each individual, we limited V and J germline allele calls

to those present in the germline on a per-individual basis. To enrich for antigen-naïve BCR sequences, we

selected those containing V and J segments that matched germline allele sequences with 100% identity,

unlikely to have undergone somatic hypermutation (SHM) (i.e. unmutated). The opposite approach was used

to enrich for antigen-experienced BCR sequences, for which either the J or V (or both) segment varied from

the germline allele sequence (i.e., were mutated). Importantly, personalized germline sets allowed us to

account for the presence of previously undocumented alleles, and thus more accurately infer SHM. The usage

frequencies of V and J genes among all unmutated or mutated unique BCR sequences were calculated for

each individual. Together, these datasets allowed us to resolve comprehensive variant callsets to perform

genetic association analyses with gene usage variation observed in the expressed light chain Ab repertoires.

Light chain gene usage is strongly associated with common IGK and IGL genetic variants in both antigen naive and experienced repertoires

Throughout the genome, genetic variation has been associated with molecular traits such as gene
expression and splicing [35–38]. We previously demonstrated that genetic variants in the IGH locus mediate the
composition of peripheral IgM and IgG repertoires through effects on IGHV, IGHD, and IGHJ gene usage [12].
Here, we followed this same quantitative trait locus (QTL) framework to test if light gene usage was associated
with IGK and IGL variant genotypes in *cis*. Allele assignments to AIRR-seq reads were derived from a
personalized germline allele set for each individual. This permitted disambiguation of IGK gene paralogs for
individuals wherein each allele of a proximal paralog was distinct from each allele of the distal paralog,
including IGKV1-12 and IGKV1D-12, IGKV1-13 and IGKV1D-13, and IGKV6-21 and IGKV6D-21
(**Supplementary Table S5**). Paralog pairs for which at least 160 individuals could not be disambiguated
included IGKV1-33/1D-33, IGKV1-37/1D-37, IGKV1-39/1D-39, IGKV2-28/2D-28, and IGKV2-40/2D-40, and are
referred to as ambiguous or "ambi" (e.g. IGKV1-39/1D-39 is IGKV1-39ambi).

We performed genetic association tests on unmutated ("antigen naive") and mutated ("antigen
experienced") sets separately to identify *cis* effects in each of the two repertoire sets. In total, our analysis
included 41 IGKV, 5 IGKJ, 33 IGLV, and 4 IGLJ genes; 2792 SNVs and 2 SVs in IGK; and 5198 SNVs and 1
SV in IGL. In the unmutated IGK repertoire, after Bonferroni multiple-testing correction (P < 5.0e-05), we
identified 2,413 unique variants (2,411 SNVs, 2 SVs) that were statistically associated with gene usage
changes in 25 (60%) IGKV and 3 (60%) IGKJ and genes (**Fig. 1, Supplementary Table S6**). In the unmutated
IGL repertoire, a set of 918 unique variants (917 SNVs, 1 SV) were associated with gene usage changes in 22
(67%) IGLV genes and 3 (75%) IGLJ (**Fig. 1, Supplementary Table S6**). Notably, a large fraction of the
genes identified in both the IGK (n=14 genes) and IGL (n=19 genes) unmutated repertoires also had significant
gene usage QTLs (guQTLs) in the mutated repertoires (**Supplementary Figures 7-9**, **Supplementary Table
S7**). However, guQTLs in the unmutated repertoires tended to have lower *P* values and explain more variance
(R^2) in gene usage (**Supplementary Fig. 7**). We also noted stronger genetic effects in IGK relative to IGL; this
included the observation that overall genetic similarity among subjects associated with more highly correlated
IGK gene usage, a signal that was blunted in IGL (see **Supplemental Material, Supplementary Fig. 10**).
Together, these results show that usage of IG light chain genes is broadly impacted by germline genetic
variants, and while these genetic effects are more prominent in the antigen naive repertoire, for many genes,
those effects persist even following antigen exposure.

Figure 1. IGK and IGL variants impact gene usage in the naïve Ab repertoire

(**A**) General structure of V and J genes in the IGK and IGL loci, including location of the recombination signal sequences

(RSS). (**B-C**) Per gene (x axis, all panels) statistics from linear regression guQTL analysis for the repertoire of unmutated

IGK (B) and IGL (C) light chains, including: (i) the number of associated variants after Bonferroni correction (IGK; P <

3.7e-5, IGL; P < 1.9e-5), (ii) −log10(P value) of the lead guQTL, (iii) adjusted R^2 for variance in gene usage explained by

the lead guQTL, (iv) the location and (v) type of variant for the lead guQTL and (vi) the fold change in gene usage

between genotypes at the lead guQTL. Summary statistics are provided in **Supplementary Table S6**.

Genomic locations of guQTLs implicate genetic roles in coding and non-coding driven processes

underlying antibody repertoire formation

Features of IG J genes include a single exon and RSS sequence, whereas V genes include an RSS

sequence, first exon, intron, and second exon that encodes the variable region (V-region) (**Fig. 1A**). While the

majority of lead guQTLs across the unmutated repertoires were intergenic (n=22 (79%), IGK; n=22 (85%),

IGL), coding lead variants were identified for 7 IGK genes (IGKJ3, IGKV2-29, IGKV1-5, IGKV1-13, IGKV2D-29,

IGKV1D-13, and IGKV1-39ambi) (**Fig. 1B**, **Supplementary Fig. 8**) and 3 IGL genes (IGLV8-61, IGLV5-48,

IGLV3-21) (**Fig. 2C, Supplementary Fig. 7**). In addition, 1 IGK lead guQTL and 3 IGL guQTLs fell within

RSSs; these were lead variants for IGKV1-6, IGLV5-37, IGLV3-16, and IGLV5-48 (**Fig. 1C, Supplementary**

Fig. 7).

Examples of lead guQTLs in coding, RSS, and intergenic regions are shown in **Fig. 2**, including IGKV2-

29, IGKV1-5, IGLV3-16, and IGLV9-49. The SNV-driven guQTL in this dataset with the lowest P value was for

IGKV2-29 (*P* value = 2.1e-58, **Fig. 2A**). This variant introduced a stop codon in V-region amino acid position 93

(**Fig. 2B**), resulting in decreased usage of IGKV2-29 (**Fig. 2C**). We also identified a lead guQTL associated

with missense variants. In the case of IGKV1-5, two linked lead guQTLs (r^2 = 1) within codon 50 associated

with a lysine to aspartic acid (<u>AA</u>G→<u>GA</u>T, K50D) change, resulting in an alteration of residue charge (**Fig. 2D-**

E). Individuals homozygous for K50 alleles, which represented six different IGKV1-5 coding alleles in this

cohort, had lower gene usage (**Fig. 2F-G**). As an example of a guQTL in the RSS, two lead variants in perfect

LD were identified at positions 8 and 23 of the spacer for IGLV3-16 (**Fig. 2H-J**). The reference haplotype had a

C at position 8, which was represented among consensus bases (C and T) at this position (**Supplementary**

Fig. 11), whereas the alternate haplotype had a G (**Fig. 2J**). Among the C/C and G/G lead guQTL genotype

groups, IGLV3-16 usage varied 3.8-fold on average (**Fig. 2K**). As noted above, the majority of lead guQTLs in

this dataset were in non-coding regions. For example, the lead guQTL for IGLV9-49 was 86 bp upstream of the

first exon, and guQTLs were not identified in coding sequence or the RSS (**Fig. 2L**). Mean IGLV9-49 usage

varied by 3.5-fold between homozygous-reference and homozygous-alternate individuals at this lead guQTL

(**Fig. 2M**). Consistent with previous observations in IGH [12], many guQTLs within IGL overlapped curated

transcription factor binding sites, representing an enrichment over background SNVs (see **Supplementary Material, Supplementary Figures 12-13**), suggesting likely roles for non-coding variants in the regulation of V(D)J recombination. Additionally, in IGK, we noted that both coding and non-coding regulatory variants altered proximal and distal gene usage biases (see **Supplementary Material, Supplementary Figures 14-15**).

Finally, in addition to SNV guQTLs, SVs resulting in gene copy number changes also made significant impacts on gene usage. Specifically, SVs were lead guQTLs for the genes IGKV1-NL1, IGKV1D-8, and IGLV5-39. In all cases, differential usage between genotypes followed an additive model in which gene usage increased with every additional haploid gene copy (**Fig. 2N**). The lead variant associated with IGKV1D-8 usage was the SV deletion of the entire IGKV distal region (see **Supplementary Fig. 4**). We noted that the number of diploid IGLJ2-3 cassette copies associated with the usage of IGLJ1 and IGLJ2-3ambi (**Supplementary Fig. 16**); however, this CNV was not the lead QTL for these genes. The complexity of this SV will likely require analysis in larger cohorts and more detailed assessment of potential haplotype-specific effects.

In summary, these results indicate that many forms of genetic variation are associated with gene usage variation in the IGK and IGL repertoire. The variable localization of guQTLs in intergenic, RSS, and coding regions implicates causative roles for these genetic variants in plausibly regulating V(D)J recombination, transcription, and translation, as well as contributing to differential heavy-light chain pairing dynamics and antigen selection.

Figure 2. Examples of coding and non-coding lead guQTLs

(**A**) Manhattan plot showing the −log10(P value) for all SNVs in IGK tested for association with usage of IGKV2-29, with SNVs colored according to LD (r^2) with the lead variant (marked with an X). (**B**) Sequence alignment of the germline IGKV2-29 alleles in this cohort from codons 90 to 95, with the lead variant indicated. Alleles encoding C93 and X93 (STOP codon) alleles are indicated. (**C**) Boxplot of IGKV2-29 usage in lead guQTL genotype groups. (**D**) Manhattan plot of associations (−log10(P value)) between all IGK SNVs and usage of IGKV1-5, with SNVs colored according to LD (r^2) with the lead variant. (**E**) Sequence alignment of the reference and alternate haplotypes at the lead guQTL, with two missense variants in perfect LD in codon 50 indicated, resulting in K50D in the alternate haplotype. (**F**) Boxplot of IGKV1-5 usage in lead guQTL (shown in (**E**)) genotype groups. (**G**) Alignment of translated germline IGKV1-5 alleles with codon 50 boxed. (**H**) Manhattan plot of associations (−log10(P value)) between all IGL SNVs and usage of IGLV3-16, with SNVs colored according to LD (r^2) with the lead variant. Two lead variants in perfect LD are in the RSS spacer. (**I**) Sequence of the RSS spacer in reference and alternate lead guQTL haplotypes. (**J**) Boxplot of IGLV3-16 usage in lead guQTL genotype groups. (**K**) (Top) Manhattan plot of associations (−log10(P value)) between all IGL SNVs and usage of IGLV9-49, with SNVs colored according to LD (r^2) with the lead variant. (Bottom) Zoom-in on an 8 Kbp window centered on IGLV9-49 with the lead non-coding variant indicated. (**L**) Boxplot of IGLV9-49 usage in lead guQTL genotype groups. (**M**) Gene usage boxplots of genes for which the lead variant was a deletion ("DEL") SV, including IGKV1-NL1, IGKV1D-8, and IGLV5-39.

guQTLs within large linkage disequilibrium blocks in IGK create expansive networks of genes with correlated usage

In our previous study of IGH guQTLs, we observed that many SNVs were associated with the usage of individual genes. This included instances in which genes and associated guQTLs extended 10's to 100's of Kb; notably, these genes exhibited correlated usage patterns [12], suggestive of coordinated gene regulation. We sought to investigate whether similar features were present in the IGK and IGL loci.

First, we observed a difference between the number of guQTLs associated with IGK versus IGL gene usage in the unmutated repertoires. In IGK, the maximum number of associations with a single gene was 1,674, with 7 genes having over 400 (mean = 407) guQTL variants. By contrast, the maximum number of guQTL variants associated with a single IGL gene was 208 (mean = 47) (**Fig. 1B-C**). This was not simply explained by the number of SNVs genotyped in the two loci, as we identified twice as many common variants in IGL relative to IGK. Thus, among all common SNVs in each locus, 84.5% in IGK and 17.7% in IGL were significantly associated with usage of at least one gene (**Fig. 3A**). For IGK, we found that a large fraction of these guQTL variants were shared between at least two genes (n=2,049, 83.9%). This was in contrast to IGL, in which we only observed 254 (22.8%) IGL guQTL variants associated with >1 gene (**Fig. 3B**). Likewise, at gene-level, 16 of 23 IGK guQTL genes shared at least one significant variant with >5 other genes. In contrast,

0/26 IGL genes shared significant guQTL variants with >5 genes. The majority of IGL guQTL genes (24 of 26)

shared variants with fewer than 3 other genes (**Fig. 3C**).

To visualize these relationships between genes and guQTLs, we constructed networks in which nodes

represented genes and edges represented connections between genes sharing at least one guQTL SNV.

From these networks, we identified multi-member cliques, in which 2 or more genes were connected by at

least one shared guQTL. For IGK, 21 of the 23 guQTL genes formed a single super clique, with embedded

subcliques in which all genes were connected to one another through guQTL variants (**Fig. 3D**). Demonstrative

of interconnected gene usage, the largest subclique was composed of 9 guQTL genes associated with a single

guQTL SNV (**Fig. 3E**). In contrast to IGK, 13 of the 26 guQTL IGL genes were represented by 4 distinct

cliques, all of which were smaller than the large clique observed in IGK and disconnected from one another

(gene membership range = 2-5; **Fig. 3D**).

The stark difference in IGK and IGL clique sizes (**Fig. 3D**) suggested likely differences in the genetic

haplotype structure between the two loci. To explore this, we estimated pairwise linkage disequilibrium (LD)

between all common SNVs (MAF >= 5%) and determined blocks of LD [39,40] (**Supplementary Table S9**, see

Methods). LD was more extensive in IGK (**Fig. 4A**) relative to IGL (**Fig. 4B**), with LD blocks >20 Kbp

comprising 53.5% and 12.9% of the IGK and IGL loci, respectively, (**Fig. 4C, Supplementary Table S10**). In

contrast, 24.4% of IGL was within LD blocks <5 Kbp, compared to only 8.6% of the IGK locus (**Fig. 4C**). The

three largest LD blocks in IGK were 122 Kbp, 110 Kbp, and 76 Kbp, compared to the three largest LD blocks in

IGL that were 34 Kbp, 26 Kbp and 24 Kbp (**Fig. 4D**). As expected, the number of SNVs per block was

positively correlated in both loci. Additionally, larger sets of genes in IGK fell within large LD blocks. We found

that 27 of 47 IGKV genes were within LD blocks >20 Kbp, whereas 5 of 39 IGLV genes were within LD blocks

>20 Kbp (**Fig. 4F**). We also noted that 26 of 47 IGKV genes were within one of 6 LD blocks containing >1

gene, in contrast to IGL (**Supplementary Fig. 17**), in which this was true for only 7 of 33 IGLV genes

(**Supplementary Fig. 18**). IGK guQTL SNVs were also more frequently in large LD blocks as 1,181 (49%)

were in blocks >20 Kbp, whereas 233 (17%) IGL guQTL SNVs were in blocks >20 Kbp (**Fig. 4G**).

These data demonstrate that a larger proportion of IGK sequence, genes, and guQTLs are contained

within large LD blocks as compared to IGL. The overlap of LD blocks with guQTL and gene cliques suggests

that extended haplotype structures within both loci likely contribute to coordinated gene regulation.

Figure 3. Genetic coordination of IG light chain gene usage is more prevalent in IGK relative to IGL

(**A**) Stacked bar plot showing the proportion of total IGK and IGL common SNVs that are a guQTL. (**B**) Bar plot showing the number of IGK and IGL SNVs (guQTLs) significantly associated with varying numbers of genes (n = 1–9). For IGK, this includes a large number of SNVs (n=2,049) that were associated with >1 gene. (**C**) For each gene, the number of genes sharing at least one guQTL variant is plotted for indicated IGK (left) and IGL (right) genes (x-axis). (**D-E**) Network analysis identified a large clique of genes and guQTLs in IGK (**D**) and 4 cliques for IGL (**E**), demarcating groups of genes associated with overlapping sets of guQTLs. For each clique, genes are shown as nodes, connected by edges color coded according to the number of shared guQTL variants.

Figure 4. IGK has larger LD blocks and lower density of SNVs relative to IGL

(**A-B**) LD heatmaps of the IGK (A) and IGL (B) loci. LD blocks are illustrated as triangles. (**C**) Stacked bar plot of the percent of each locus (IGK, IGL) that is within LD blocks of various lengths (colors). (**D**) Plots of LD blocks in IGK and IGL depicting the length of each block (y-axis) and number of SNVs in each blot (x-axis). (**E**) Bar plot of the overall SNV density in the IGK and IGL loci. (**F-G**) Barplots of the counts of IGK (**F**) or IGL (**G**) genes in LD blocks with lengths indicated along y-axes.

guQTLs are linked to missense variation in coding regions and physicochemical CDR3 properties in the IGK and IGL repertoires

Together, the data presented so far demonstrate that genetic variants within IGK and IGL associate with shifts in gene usage in the light chain repertoire. While the majority of lead guQTLs in both loci occurred in intergenic space, we wanted to see whether genetically driven usage shifts also associated with: 1) germline changes in V gene coding sequence spanning complementarity determining and framework regions (CDR1, CDR2, FWR1, FWR2, and FWR3); and 2) amino acid properties of CDR3 sequences spanning germline codons and junctions of recombined V and J genes. We reasoned that such associations would link changes in gene usage to BCR features likely to impact preferential pairing of available heavy and light chains and antigen binding. This has direct relevance to germline variants contributing to Abs associated with disease and vaccination [20–22,24–26,41].

First, we found that many lead guQTLs were associated with shifts in coding allele usage within the repertoire, representing LD between coding and non-coding SNVs. This was consistent with our previous investigation of IGH guQTLs [12]. Specifically, for 18/32 (56%) tested IGK genes, individuals within different guQTL genotypes exhibited differential coding allele frequencies (Fisher's exact test, Bonferroni; $P < 0.002$). Likewise, in IGL we noted such associations for 9/24 (38%) guQTL genes (Fisher's exact test, Bonferroni; $P < 0.002$) (**Fig. 5A-B**, **Supplementary Table S11**). Among these genes, the 12/18 (66%) in IGK, and 7/9 (77%) in IGL involved alleles carrying amino acid changes (**Fig. 5C-D**). For the remaining genes in each locus, genes either exhibited allelic variation, but did not associate with guQTL genotype, or lacked appreciable allelic variation (major allele frequency >95%; **Fig. 5C-D**). Examples of genes with coding allele variation linked to lead non-coding guQTL variants include IGKV2-30 and IGLV7-46, for which gene alleles were distributed differently among the non-coding lead guQTL genotypes (**Fig. 5E-F**). In the case of IGKV2-30, the *02 allele, which harbored a missense variant in CDR1, was carried by 95.9% of individuals with genotype A/A at the lead guQTL variant, compared to only 7.9% of individuals with genotype G/G (**Fig. 5E**). Likewise, in the case of IGLV7-46, the *02 allele, which harbored an amino acid change in FWR3, was carried by 100% of individuals with guQTL genotype G/G and by 0.7% of individuals with genotype C/C (**Fig. 5F**).

We next asked whether shifts in gene usage also resulted in shifts in CDR3 physicochemical properties. To do this, we conducted an unbiased test for associations between variation in nine CDR3 properties and genotypes at all variants across IGK and IGL (**Supplementary Table S12**). In IGK, we identified SNVs associated (Bonferroni, $P < 3.9e-05$) with CDR3 properties of aromaticity, aliphaticity, acidity,

polarity, bulk, and GRAVY index (**Fig. 6A; Supplementary Fig. 19**). Likewise, in IGL, SNVs were associated (Bonferroni, *P* < 1.9e-05) with CDR3 aromaticity, aliphaticity, GRAVY index, bulk, basicity, polarity, charge, and length (**Fig. 6B; Supplementary Fig. 20**). Lead variants in both loci overlapped guQTLs, linking CDR3 properties with gene usage variation. For example, the lead variant associated with IGK CDR3 aromaticity was also a guQTL for seven IGKV genes (**Fig. 6A, 6C-E**) that are part of a previously described network clique (**Fig. 3D**). Among these genes, we focused on those with usage patterns that were negatively correlated, and thus considered to differentially represent the guQTL genotypes. Specifically, IGKV1-13/1D-13 usage was highest in individuals with high CDR3 aromaticity. In contrast, the usage of IGKV2-40ambi, IGKV1-39ambi, and IGKV1D-12 were highest in individuals with low CDR3 aromaticity (**Fig. 6D-E**). To determine whether these genes explain CDR3 aromaticity variation between genotype groups, we computed CDR3 aromaticity for BCRs utilizing only IGKV1-13/1D-13, IGKV2-40ambi, IGKV1-39ambi, or IGKV1D-12 (**Fig. 6F**). This demonstrated IGKV1-13/1D-13-encoded BCRs had higher aromaticity than those encoded by all of the other three genes. This was regardless of the J gene contribution (**Supplementary Fig. 20**), indicating the genetic effect on CDR3 aromaticity is through influence on V gene usage.

In IGL, CDR3 aliphaticity and aromaticity shared the same lead variant; this variant was also the lead guQTL for both IGLJ1 and IGLJ2-3ambi, linking genetic regulation of IGLJ gene usage with CDR3 properties (**Supplementary Fig. 21**). At this variant, A/A individuals had relatively higher CDR3 aliphaticity and IGLJ2-3ambi usage, whereas G/G individuals had relatively higher CDR3 aromaticity and IGLJ1 usage. Analysis of BCRs using one or the other of these IGLJ genes revealed that sequences containing IGLJ2-3ambi have relatively high CDR3 aliphaticity, whereas sequences containing IGLJ1 have relatively high CDR3 aromaticity (**Supplementary Fig. 21**). Together, these data link genetic effects on IGLJ gene usage with IGL CDR3 properties.

In summary, 41% of IGLV and 63% of IGKV genes showed significant variation in coding alleles among lead guQTL genotype groups, indicating LD between non-coding variants and gene alleles. Additionally, we show that variation in gene usage also contributes to biases in CDR3 properties, at least in part explained by contributions of germline encoded amino acids at the 3' of V genes and 5" end of J genes. This is noteworthy, as it indicates that guQTLs not only impact general variation in gene usage, but also have the potential to modulate the availability of germline encoded residues in the baseline unmutated repertoire.

Figure 5. Linkage between IGKV and IGLV coding region alleles and lead guQTL genotypes

(**A-B**) Variation in the proportion of different coding gene alleles among lead guQTL genotype groups was determined by Fisher's exact test for guQTL genes in IGK (**A**) and IGL (**B**). Barplots shows -$\log_{10}$(P value). (**C-D**) For each gene, the frequency of coding alleles in the cohort is shown, with unique alleles color coded. Genes that lack appreciable allelic variation (major allele frequency >95%) are indicated with an asterisk. Circles above each gene indicate whether coding allele variation is linked to the lead guQTL. guQTLs linked to coding allele variation are associated with missense or nonsense variants. (**E-F**) Stacked bar plots showing the distributions of the respective coding allele genotypes across individuals partitioned by guQTL genotype for IGKV2-30 (**E**) and IGLV7-46 (**F**).

Figure 6. IGK and IGL variants impact CDR3 physicochemical properties in the naïve Ab repertoire

(**A-B**) For each CDR3 physicochemical property (x-axis), mean values were computed for each individual and tested for association (linear regression) with all common variants in IGK (**A**) and IGL (**B**). Barplots show (i) the number of QTL variants (Bonferroni-corrected) for each property, (ii) the -log10(P value) for lead variants, and (iii) the number of guQTL genes identified for the lead CDR3 property QTL variant. Summary statistics are provided in **Supplementary Table S12**. (**C**) Manhattan plot shows the −log10(P value) for all SNVs in the IGK locus tested for association with CDR3 aromaticity, with QTLs colored dark red and the lead QTL labelled. (**D**) Boxplot of the mean IGK CDR3 aromaticity with individuals separated by genotype at the lead QTL. (**E**) Boxplots of usages for seven IGK genes that are guQTLs at the lead CDR3 aromaticity variant. (**F**) BCR sequences that used the indicated V genes were selected from the Ab repertoire, then mean CDR3 aromaticity of each repertoire subset was computed and plotted with individuals separated by genotype at the lead CDR3 aromaticity QTL.

Discussion

Akin to other hypervariable immune loci, the IG loci exhibit extensive haplotype diversity at the population level, and are among the most structurally complex regions in the human genome [12,14,15,33,42]. This complexity has limited our ability to accurately characterize inter-individual IG haplotype diversity and delineate its role in shaping the composition of the Ab repertoire [41]. Here, by leveraging the strengths of long-read sequencing, we were able to overcome this barrier. We characterized complete genotype callsets for SNVs and SVs across the IGL and IGK loci, and combined these with matched light chain repertoires. First, this comprehensive dataset allowed for the discovery of tremendous population-level genetic variation within the IGK and IGL loci, including descriptions of novel SNVs, SVs, and coding alleles. These discoveries alone will now facilitate significant improvements in existing germline database resources for the IG loci (Peres et al., *in prep*). Second, for the first time, we were able to directly utilize personalized germline reference sets for each individual to increase the accuracy of V, D, and J gene/allele assignments, including resolution of duplicated paralogs between the proximal and distal duplicated regions of the IGK locus. Third, with these data in hand, we expanded our previous work in IGH [12] to demonstrate that IGK and IGL polymorphisms also contribute to variation in light chain repertoire gene usage and associated changes in the composition and availability of V, J, and CDR3 encoded amino acids among expressed Ab transcripts. Together, these findings solidify the pervasive impact of IG genetics on the adaptive immune system.

Across the IGK and IGL loci, genetic variants were statistically associated with usage variation in the majority of V and J genes. For a subset of IGKV genes, for example, we found that even single guQTLs could explain over 75% of the usage variation among donors. Notably, however, although we found that most guQTLs and associated genes were common between unmutated and mutated repertoires, the extent of variance in gene usage explained by guQTLs in the unmutated repertoire was on average higher for both IGK and IGL; V genes also had stronger genetic associations relative to J genes in both loci. The blunted genetic effects in the mutated repertoire may reflect shifts in usage in the memory repertoire driven by interactions with

antigen. However, it is notable that even in antigen-experienced repertoires, variation can still be explained by

genetic factors, indicating some degree of genetic constraint, consistent with observations in IGH [12,16]. We also

noted that on average, R^2 values were lower in IGL; however, because this analysis only included an

assessment of lead guQTLs, we have not accounted for additional variants that may make additional genetic

contributions. We previously showed that secondary guQTLs in IGH were able to increase the variance in gene

usage explained by *cis* genetic factors [12]. As cohorts increase in size, we expect it will be possible to

characterize additional guQTLs in IGK and IGL.

An assessment of guQTL positions within each locus provided initial evidence of the mechanisms by

which they may exert their effects on the repertoire. Early studies in IGK were the first to show that IG

polymorphism can directly impact the usage of particular genes in the repertoire. These specifically linked

variation within the RSS of IGKV2D-29 and its usage frequency [28,43,44], demonstrating that RSS polymorphisms

have the potential to influence the binding of RAG1/2 and the selection of genes by V(D)J recombination. Here,

we found additional direct evidence for effects of RSS variants on several IGK and IGL genes. However,

consistent with previous observations in IGH [12], the majority of light chain guQTLs were intergenic SNVs. The

factors underlying the effects of non-coding guQTLs require further study, but are expected to influence various

regulatory mechanisms (e.g., enhancer and promoter and function; formation of topologically associating

domains) in the IG loci during V(D)J recombination [45–49]. It is notable that in IGL we observed overlap between

a subset of intergenic guQTLs and known TFBSs (**Supplemental Fig. 12**); this included enrichments in

binding sites for CTCF, a transcription factor known to be critical to the chromatin landscape within IG loci [50].

We also found that SVs were the lead guQTLs for three genes (IGKV1D-8, IGKV1-NL1, and IGLV5-39). In all

cases these SVs altered the number of diploid copies (range = 0-2) and thus the chance they could be

selected by V(D)J recombination. We identified multiple less common SVs (MAF <5%) that will require study in

larger sample sizes to more fully assess their contribution to gene usage. Overall, however, we noted that the

number of genes impacted by SVs in each of the light chain loci were comparatively fewer than reported in IGH

[12], which is likely a reflection of the fact that the IGH locus overall has a greater number of SVs.

We also observed examples in which guQTLs were localized to intronic and V gene coding sequences,

the latter of which included examples resulting in the introduction of premature stop codons and amino acid

changes. These examples indicate that, rather than effects on V(D)J recombination, some guQTLs potentially

influence the light chain repertoire composition by impacting transcription and translation, with implications for

light chain selection during B cell development. For example, we would expect that B cells expressing non-

functional alleles would undergo receptor editing and/or negative selection in the bone marrow, leading to their

absence in the periphery [51–53]. Likewise, it is plausible that some light chain coding alleles within an individual

may serve as less optimal partners for rearranged heavy chains [54], leading to a decrease in their frequency

within the mature naive repertoire. This would be somewhat analogous to shifts in light chain gene distributions

noted in the memory repertoire, which have been attributed to light chain coherence [55]. However, fully

delineating the roles of genetics in heavy and light pairing and in the context of different antigen-driven effects,

will require careful investigation of guQTLs across developmental time points, and will need to consider

combined effects of polymorphisms across the three loci.

To date, differences in the genetic architecture of the IGK and IGL loci have been underexplored.

Previous comparisons of a small number of IGK and IGL haplotypes indicated that SNV densities were lower in

IGK compared to IGL [31]. Our data confirmed this pattern at the population level, revealing that the number of

common SNVs was almost 2-fold higher in IGL. Additionally, we found that IGL was also characterized by less

extensive LD. These stark differences in genetic architecture were reflected in the interconnectedness of gene

usage profiles in the repertoire, specifically that a greater proportion of genes in the IGK repertoire shared

overlapping guQTLs. This suggests that we could expect the regulatory landscapes to also be different. To

date, our knowledge of V(D)J regulation in the light chain loci come from studies in mice; however, it is unlikely

that we can extrapolate much detail from these studies, as these loci show little structural resemblance to

those in humans. Given the ordered engagement of IGK and IGL genes in the formation of functional BCRs

during B cell development, it's plausible that the differences in genetic structure have been shaped by their

differing functional roles. Recent work looking at IG locus genetic features across a range of vertebrate species

suggest co-evolution of the light chain loci [56].

These data highlight the impacts of germline variation on gene usage variation in the repertoire, and

their underlying mechanisms. We argue that the influence of genetics should be considered when seeking to

understand how inter-individual differences in repertoire composition directly contribute to antigen-driven

responses [19–22,24,57–62]. Given coding differences between genes, usage variation by default alters the

landscape of available germline encoded residues among expressed BCRs, which can also bias SHM patterns

[63]. Here, we demonstrate that guQTLs are also directly linked to amino acid differences between alleles of

individual genes; thus, while some coding variants may be present within the genome of an individual, their

frequency within the repertoire is dependent on guQTL genotype. Taking this a step further, we showed that

gene usage also correlated with variation in CDR3 properties, driven by direct contributions of 3' V and 5' J

gene germline-encoded bases to junction amino acids. This is consistent with observations of CDR3

comparisons between monozygotic twins and unrelated individuals [17]. The link between guQTLs and amino

acid features among expressed light chain transcripts elevates the likelihood that guQTLs significantly impact

the antigen-binding landscape of expressed Abs.

Together, these findings advance our basic understanding of repertoire development, illuminating

regions of IGK and IGL that not only regulate gene usage but establish biases in the amino acid diversity

observed among expressed Abs. In combination with our previous work in the IGH locus, our data lay a

foundation for integrating genetic contributions from all three IG loci to establish more complete and precise

models of sequence diversity in the expressed repertoire. This will be critical for refining our understanding of

Ab repertoire dynamics in health and disease.

Materials and Methods

Sample information

PBMCs (n=177) were procured from STEMCELL Technologies (Vancouver, Canada). Sample-level demographic information, including age, biological sex, and ancestry informative marker (AIM)-determined ancestry are reported in **Supplementary Table S1**.

Single-molecule real-time (SMRT) long-read library preparation and sequencing

DNA was extracted from ~3-5 million PBMCs per donor using the DNA/RNA co-extraction AllPrep kit (Qiagen, Germantown, MD, USA), and genomic DNA was processed using our published "IG-capture" targeted long-read sequencing protocol [12–15]. Briefly, high molecular weight DNA (~2.5 µg) was sheared to ~15 Kbp using g-tubes (Covaris, Woburn, MA, USA) and size-selected using Pippin systems (Sage Science, Beverly, MA, USA) using the "high pass" protocol to select fragments greater than 5 Kbp. Size-selected DNA was ligated to universal barcoded adapters and amplified, and small fragments and excess reagents were removed using 0.7X KAPA Pure beads (Roche, Indianapolis, IN, USA). Individual samples were pooled in groups of six prior to IGK and IGL enrichment using custom Roche HyperCap DNA probes described previously [14,15]. Targeted fragments were amplified after capture to increase total mass for sequencing library construction.

Enriched IGK and IGL libraries were prepared for sequencing using the SMRTBell Express Template Prep Kit 2.0 (Pacific Biosciences, Menlo Park, CA, USA) and SMRTBell Enzyme Cleanup Kit 1.0 (Pacific Biosciences), according to the manufacturer's protocol. Resulting SMRTbell libraries were multiplexed in pools of 12 and sequenced using one SMRT cell 8 M on the Sequel IIe system (n=134) (Pacific Biosciences) using 2.0 chemistry and 30-hour movies. For Revio sequencing (n=43), SMRTbell libraries were pooled in 36-plexes and sequenced using one SMRT cell 25M on the Revio system (Pacific Biosciences) using Revio Polymerase Kit v1.0 (PacBio; 102-739-100) and 30 hour movies. High Fidelity ("HiFi") intramolecular circular consensus reads with accuracies >99.9% (Q20) were generated on instrument and used for all downstream analyses.

IGK and IGL AIRR-seq

AIRR-seq libraries were prepared and sequenced for 173 individuals (IGK) 171 (IGL). RNA was extracted from ~3-5 million PBMCs per donor using the AllPrep DNA/RNA Kit (Qiagen). AIRR-seq libraries were generated using a 5' Rapid Amplification of cDNA Ends (RACE) approach. For IGK and IGL 5'RACE AIRR-seq, libraries were produced using the SMARTer Human BCR Profiling Kit (Takara Bio, San Jose, CA, USA), according to the manufacturer's instructions. Quality and quantity of individually indexed IGK libraries were determined using the 2100 Bioanalyzer High Sensitivity DNA Assay Kit (Agilent, Santa Clara, CA, USA) and IGL libraries with the Qubit 3.0 Fluorometer dsDNA High Sensitivity Assay Kit (Life Technologies, Carlsbad, CA, USA). Libraries were pooled at 10 nM and sequenced on the Illumina NextSeq system using

531   300 bp paired-end reads with the 600-cycle NextSeq P1 Reagent Kit (n=161) or with the 600-cycle MiSeq

532   Reagent Kit v3 (n=11) (Illumina, San Diego, CA, USA).

Construction of a custom linear reference assembly

We used our previously described custom linear reference [15], which includes modifications to the IGH

[12,13] and IGK [15] loci to include sequences not present in the GRCh38 assembly. To include IGL sequences not

present in GRCh38, chromosome 22 was removed and replaced with the T2T (CHM13v2.0) chromosome 22,

including the IGLV5-39 structural variant (SV, insertion) sequence. In addition, 46,423 bp of sequence

(chr22:23315600-23362023) is from a Human Pangenome Reference Consortium (HPRC) haplotype from

sample HG00621, which includes a 16,093 bp insertion relative to the CHM13v2.0 reference, reflecting 3

additional copies of the IGLJ-C3 cassette relative to the CHM13v2.0 reference. This reference is publicly

available at https://github.com/Watson-IG/immune_receptor_genomics/tree/main.

Phased assembly of IGK and IGL

Phased assemblies were generated as described previously [15]. HiFi reads were used to generate

haplotype-phased *de novo* (i.e. reference-agnostic) assemblies using hifiasm [64] (v0.18.2-r467) with default

parameters. For each sample, hifiasm contigs were concatenated into a FASTA file, then redundant contigs

were filtered out using the seqkit toolkit [65] command 'seqkit rmdup --by-seq <hifiasm_contigs.fasta>' (seqkit

v2.4.0). Hifiasm contigs were mapped to the custom reference assembly using minimap2 (v2.26) with the '-x

asm20' option. HiFi reads were also processed using IGenotyper [13]; the programs "phase" and "assemble"

were run with default parameters to generate phased contigs and HiFi read alignments to the custom

reference.

For each sample, aligned HiFi reads as well as aligned hifiasm-generated contigs and IGenotyper-

generated contigs were viewed in the Integrative Genomics Viewer (IGV) application [66] for manual selection of

phased contigs. Contigs were evaluated for read support from mapped HiFi reads, and contigs harboring one

or more SNVs that lacked read support were not selected during manual curation. Where a hifiasm and an

IGenotyper contig were identical throughout a phased block, the hifiasm contig was selected, as described

previously [15]. Curated, phased assemblies were aligned to the custom reference using minimap2 [67] with the '-x

asm20' option.

To assess accuracy of manually curated assemblies, personalized references were first generated by

N-masking the IGK (chr2:88837160-90280100) and IGL (chr22:22378775-23423320) loci of the custom

reference and, for each sample, appending the reference FASTA with IGK and IGL curated contigs. All HiFi

reads from each individual were aligned to the corresponding personalized reference using minimap2 with the

'-x map-hifi' preset; coverage and read length metrics were extracted from these alignments. Positions in

assemblies with > 25% of aligned HiFi reads mismatching the assembly were identified by parsing the output

of samtools 'mpileup' using custom scripts; assembly accuracy was determined using the formula [total

(diploid) bases without a mismatch / total (diploid) assembly length (bp)] * 100 = % accuracy (**Supplementary**
Table S1).

Identification of IGK and IGL gene alleles

Sequences corresponding to V, J, and C exons were obtained from assembly BAM files and aligned to
all known human immunoglobulin alleles from the IMGT database (version downloaded on 2023-09-26) using
custom Python scripts and functions provided by the receptor_utils library (https://pypi.org/project/receptor-
utils/). Metrics of HiFi read support for each allele were calculated using custom scripts written in Python and
bash. Briefly, for each sample, curated IGK and IGL assembly contigs were appended to our custom reference
with the IGK and IGL loci N-masked to generate a personalized reference FASTA, as described above. All HiFi
reads from IG-capture for a given individual were mapped to the personalized reference using minimap2 with
the '-ax map-hifi' preset, then the resulting BAM file was input to samtools 'mpileup' with iteration over allele
coordinates in the personalized reference. The outputs of this script are in **Supplementary Table S3** (IGK) and
Supplementary Table S4 (IGL), and include a column for total number of HiFi reads spanning the novel allele
('Fully_Spanning_Reads') and a column for the number of HiFi reads spanning the novel allele with 100%
sequence identity ('Fully_Spanning_Reads_100%_Match'). A complete description of HiFi read support
metrics for alleles is available at https://vdjbase.org/.

Genetic ancestry

IGenotyper [13] was used to call SNVs at ancestry-informative markers (AIMs) by aligning, phasing, and
locally assembling reads at AIM regions, then directly identifying SNVs from the assembled sequences.
Genetic ancestry was determined using these AIMs and the STRUCTURE program [68]. SNV VCFs were
processed to extract AIM-specific data from IG-Capture libraries using custom scripts and VCFtools. Coverage
of AIMs was assessed using BAM files and the pysam library, ensuring a minimum read depth threshold for
inclusion. Genotypes were converted into haplotypes by separating phased alleles, and samples were coded
alongside reference populations from the 1000 Genomes Project. STRUCTURE (v2.3.4) was run with K = 5,
representing five global ancestry groups (European, African, East Asian, South Asian, and American), using
default admixture and allele frequency models. For each sample, the two highest ancestry proportions were
identified. If the difference between these two proportions was less than or equal to 5%, the sample was
classified as "Mixed." Otherwise, the sample was assigned to the ancestry category with the highest
proportion.

Processing AIRR-seq data and calculating gene usage

Paired-end sequences ("R1" and "R2") were processed using the pRESTO/Change-O toolkit [69,70]. All
R1 and R2 reads were trimmed to Q = 20 using the function "FilterSeq.py trimqual". Constant region (IGKC and
IGLC) primers were identified with an error rate of 0.3 and corresponding chains were recorded in the fastq

headers using "MaskPrimers align." The 12 base UMI, located directly after the constant region primer, was

extracted using "MaskPrimers extract." Annotations between mate pairs, including UMI barcodes and constant

region calls, were synchronized using PairSeq.py to sort reads into mate pairs and remove unpaired reads.

UMI groups sharing the same barcode were processed to generate consensus sequences using the

BuildConsensus.py function. The following criteria were applied: a minimum UMI group size of one, a

maximum mismatch error rate of 10%, and at least 60% agreement on the constant region call within the

group. Reads with lower-quality consensus sequences (Q < 30) were masked using FilterSeq.py maskqual.

Duplicate counts ("Dupcounts") were recorded, and duplicate sequences were collapsed using CollapseSeq.py

to retain one representative sequence per cell, with the total number of sequences contributing to each

consensus recorded as "Conscount." Collapsed consensus sequences supported by fewer than two

contributing reads (Conscount < 2) were discarded using SplitSeq.py. Samples containing fewer than 100

unique sequences were excluded from downstream analysis; after filtering, 170 individuals were included for

IGK analyses and 170 individuals were included for IGL analyses (173 individuals total; **Supplementary Table**

S1). After processing, the repertoires contained a mean of 33,678 unique BCR sequences (IGK) and 13,281

(IGL) (**Supplementary Table S1, Supplementary Fig. 3**).

Germline allele designations were assigned to sequences using a personalized allele database during

the IgBLAST step. For each individual, IGK and IGL germline allele databases were generated from the set of

alleles identified in genomic assemblies derived from long-read sequencing. Separate BLAST databases were

created for V and J segments using makeblastdb. The resulting databases were used as input for igblastn, and

IgBLAST output files ("Change-O" tables) of unique BCRs were generated for IGK and IGL separately. This

process permitted theoretical disambiguation of IGK gene paralogs for individuals wherein the sequence of

each allele of a proximal paralog was distinct from the sequence of each allele of the distal paralog (results in

Supplementary Table S5). In the case of IGKV1-13 and IGKV1D-13, a subset of the cohort (n=114) met this

disambiguation criteria and was carried forward to identify guQTLs for these genes.

Due to sequence identity between IGKV paralog allele sequences, genes collapsed into a single

ambiguous ("ambi") entity in Change-O tables included:

1) IGKV1-37 and IGKV1D-37 replaced with IGKV1-37ambi

2) IGKV1-39 and IGKV1D-39 with IGKV1-39ambi

3) IGKV2-40 and IGKV2D-40 with IGKV2-40ambi

4) IGKV1-33 and IGKV1D-33 with IGKV1-33ambi

5) IGKV2-28 and IGKV2D-28 with IGKV2-28ambi

In addition, IGLJ gene calls that corresponded to a IGLJ2 or IGLJ3 cassette (IGLJ2, IGLJ3-1, IGLJ3-2, IGLJ3-

3, IGLJ3-4) were collapsed to "IGLJ2-3ambi".

Change-O tables of unique BCRs were analyzed using the alakazam package [70]. To enrich for antigen-

naïve BCRs, only unmutated light chain sequences with 100% identity to the assigned germline V and J alleles

were included in downstream analyses. For analysis of mutated sequences (i.e. the fraction of sequences

enriched with those containing SHM), sequences with less than 100% identity to either the germline V or J

allele were included. Gene usage was quantified for IGK and IGL light chains using the countGenes function

with the parameters gene = "v_call" and "j_call", groups = "sample_id", mode = "gene", and genes with a

sequence count (seq_count) of at least 10 in at least one sample were retained. A m × n usage matrix C was

created, where m are the genes and n are the samples. Each value in C represented usage frequency among

all unique (unmutated or mutated) BCR sequences for a given gene in a given sample.

CDR3 physicochemical properties were computed using the aminoAcidProperties function (47) with

options seq = "junction", trim = TRUE, label = "cdr3"; resulting values were then averaged across all

sequences within each sample to obtain sample-level means.

Selecting common variants for gene usage QTL analysis

SNVs were genotyped from curated assemblies as described previously [15]. Variants were called from

assemblies using 'bcftools mpileup' (bcftools v1.15.1) with options '-f -B -a QS', then 'bcftools call' with options

'-m --ploidy 2'. A mutli-sample VCF file was generated using 'bcftools merge' with the '-m both' option.

Multiallelic SNVs were split into biallelic records using the 'bcftools norm' command with options '-a -m-'. The

VCF file was annotated for V-exon, introns, L-Part1, RSS sequences (heptamer, nonamer, spacer), were

added using vcfanno and BED files corresponding to our reference (available at https://github.com/Watson-

IG/immune_receptor_genomics/). Biallelic SNVs with MAF ≥ 5% were selected using bcftools view with options

"-m2 -M2 -v snps -i 'INFO/MAF >= 0.05'" and used for guQTL analysis.

All SVs in IGKV and IGLV gene regions were genotyped by manual inspection using IGV [66]. SVs with a

MAF less than 0.05 were not included in the guQTL analysis.

Gene usage QTL analysis

Genotypes at common SNVs and SVs were tested for association with usage using linear regression to

determine significance and additional metrics (e.g., beta coefficients and R^2 values). To adjust for multiple

comparisons, a Bonferroni correction was applied on a per-gene basis. Pairwise r^2 (LD) values were computed

using vcftools '--geno-r2' [71]. Variants in complete linkage disequilibrium (LD r^2=1) were considered as a single

variant during correction, representing only one association test.

Haplotype block analysis

LD blocks were computed and visualized using "LDBlockShow" [39] using the multi-sample VCF of

common SNVs (MAF >= 5%) as input, with options '-SeleVar 2 -BlockType 1' to use normalized linkage

disequilibrium coefficients (D') as described by described by Gabriel et al. (2002) [40] to determine haplotype

blocks. The program was run using '-Region chr2:88837160-90280100' for IGK and '-Region chr22:22378775-

23423320' for IGL. LD block boundaries, sizes, and SNVs within blocks are included in **Supplementary Table**

S9. Genes overlapping LD blocks were identified using bedtools [72] 'intersect' (bedtools v2.30.0).

Network analysis

Variants significantly associated with IGK and IGL gene usage (after Bonferroni correction) were

compiled to create a set of guQTL variants for each gene. Pairwise comparisons between genes were

performed to calculate Jaccard similarity indices, defined as the ratio of shared variants to the total unique

variants across the two genes being compared. Only gene pairs with nonzero similarity (i.e., at least one

shared variant) were included in the analysis. Separate IGK and IGL network graphs were constructed and

visualized using igraph [73] and ggraph [74] (IGL),. In these graphs, nodes represented individual genes and were

positioned using the Fruchterman-Reingold force-directed algorithm, edges connected pairs of genes that

shared guQTL variants, and edges were labeled to reflect the number of shared guQTL variants.

Regulatory analysis

ENCODE transcription factor binding site data were obtained from the UCSC Genome Browser under the

group "Regulation," track "TF Clusters," and table "encRegTfbsClustered." SNVs associated with gene usage

were overlapped with this track and enrichment over all SNVs overlapping each track was calculated using a

one-sided Fisher Exact Test (**Supplementary Table S8**).

Data availability

Long-read sequencing data and AIRR-seq datasets generated in this study have been deposited in the

BioProject repository PRJNA1274485 . Previously published AIRR-seq datasets are available in the BioProject

repository PRJNA555323. Metadata and sequencing summary statistics for this study are provided in

Supplementary Table S1.

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Author Contributions

E.E., O.L.R., M.L.S., and C.T.W. contributed to the conception of the work. M.L.S. and C.T.W. directed wet

lab/bench and sequencing experiments. E.E., D.S., K.S., S.S. prepared sequencing libraries. E.E., U.J.,

O.L.R., W.L., W.S.G., A.P., G.Y. and Z.V. developed the computational pipeline to analyze the sequencing

data. E.E., G.Y., C.T.W., M.L.S contributed to and supervised the analysis and data interpretation. C.T.W. and

M.L.S. acquired funding. E.E. and C.T.W. drafted the manuscript and all authors contributed to revising the

manuscript.

Competing interests

C.T.W., M.L.S., and W.L. are founders and shareholders of Clareo Biosciences, Inc. and serve on its Executive
Board.

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