Chromatin conformation dynamics during CD4+ T cell activation implicates autoimmune disease-associated genes and regulatory elements

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ABSTRACT

Genome-wide association studies (GWAS) have identified hundreds of genetic loci associated with autoimmune disease, but the causal variants and their contribution to immune dysregulation remain largely unknown. We measured the dynamics of chromosome conformation, chromatin accessibility, and gene transcription across three phases of naive human CD4+ T cell activation and co-localized active *cis*-regulatory elements with the 95% credible set of variants from 15 autoimmune GWAS. Reorganization of chromosome structure placed these elements in direct contact with ~1,200 protein-coding genes, at least one-third of which were dynamically regulated by stimulation. The set of implicated genes is enriched for high-throughput CRISPR screen targets that control multiple aspects of CD4+ T cell activation, and we pharmacologically validated eight novel gene products as potent regulators of T cell proliferation. These maps also allowed the identification and functional validation of a novel stretch of intergenic enhancers for the autoimmune gene *IL2* whose activity is influenced by autoimmune-associated genetic variation. This study represents a powerful strategy and resource for assigning physiologic relevance to autoimmune-risk variants and identify novel genes that control T cell activation and function.

INTRODUCTION

GWAS has revealed hundreds of regions of the human genome robustly associated with autoimmune disease susceptibility. The majority of GWAS variants are located in non-coding regions of the genome, and likely contribute to disease risk by modulating cis-regulatory element (cRE) activity to influence gene expression[1]. Identifying causal variants and their corresponding effector genes molecularly responsible for increased disease risk is critical for identifying targets for downstream molecular study and therapeutic intervention. Identifying and prioritizing disease-causal variants is limited by a lack of genetic fine-mapping and functional studies that define the mechanisms of control over cRE activity and gene expression.

CD4+ T cells are key regulators of innate and adaptive immune responses that combat infection by orchestrating the activity of other immune cells. In their quiescent, naïve state, 'helper' T cells traffic between the blood and secondary lymphoid tissues as part of an immunosurveillance program maintained by transcription factors such as KLF2, TOB, and FOXO[2–4]. Upon encountering specific antigen, a cascade of signals activated through the TCR and costimulatory receptors results in large-scale changes in gene expression driven by factors like NFKB, NFAT, IRF4, and STATs, leading to proliferation and differentiation into specialized Th1, Th2, and Th17 subsets capable of participating in protective immunity[5,6]. CD4+ T cells are also key players in the induction and pathogenesis of autoimmunity. The cis-regulatory architecture of CD4+ T cells is enriched for autoimmune disease GWAS variants[7–14], and T cells from autoimmune patients harbor distinct epigenetic and transcriptomic signatures linking dysregulated gene expression with disease pathogenesis. Autoimmune variants may therefore contribute to the breakdown of immune self-tolerance by shifting the balance between autoreactive conventional vs. regulatory CD4+ T cells, by altering cytokine production, or by promoting auto-antigen production[15,16].

Chromatin conformation assays allow for identification of putative target genes of autoimmune variant-containing cRE in close physical proximity to gene promoters. Previous work using

promoter-capture HiC and HiC in combination with other epigenetic marks have implicated sets

of autoimmune variants and effector genes that may participate in T cell activation[17,18]. In addition

to chromatin conformation approaches, multiple complementary approaches have been

developed to link disease-associated variants to their downstream effector genes. Expression

quantitative trait mapping (eQTL) and chromatin co-accessibility data can be used to implicate

effector genes through statistical association of genotypes with readouts of expression or other

molecular markers[19]. However, these approaches do not account for the relevant 3D structure of

the genome in the nucleus, and are highly susceptible to *trans*-effects and other confounding

factors.

In this study, we define the impact of TCR-CD28 activation on the autoimmune-associated

cis-regulatory architecture of CD4+ helper T cells, leading to the discovery of a stretch of distal

enhancers required for normal expression of the canonical T cell activation gene *IL2* whose

activity is influenced by autoimmune risk variants. The set of variant-connected effector genes

defined by 3D physical proximity to autoimmune-associated cRE is enriched for genes that

regulate T cell activation, as validated pharmacologically in this current study and by CRISPR-

based screens reported in orthogonal studies[20–22].

RESULTS

Gene expression dynamics as a function of naïve CD4+ T cell activation

To identify the set of genes and cREs that are affected by and may contribute to CD4+

activation, we characterized the dynamics of gene expression, chromatin accessibility, and 3D

chromatin conformation in human CD3+CD4+CD45RA+CD45RO- naïve T cells purified directly

ex vivo and in response to *in vitro* activation through the T cell receptor (TCR) and CD28 for 8 or

24 hours using RNA-seq, ATAC-seq, and HiC (**Fig. 1A**). ATAC-seq and RNA-seq libraries were

prepared using CD4+ T cells derived from N=3 donors, while HiC libraries were prepared from

N=2 donors. We verified the reproducibility of replicate ATAC-seq and RNA-seq libraries with

principal component analysis and HiC libraries using distance-controlled, stratum-adjusted

correlation coefficient (SCC). Replicate samples were highly correlated and clustered by

activation stage (**Fig. S1A-C**). As expected, quiescent naïve CD4+ T cells expressed high levels

of *SELL, TCF7, CCR7,* and *IL7R*, and rapidly upregulated *CD69, CD44, HLADR,* and *IL2RA* upon

stimulation (**Fig 1B**). Genome-scale gene set variance analysis based on MsigDB hallmark

pathways showed that genes involved in KRAS and Hedgehog signaling are actively enriched in

quiescent naive CD4+ T cells, while stimulated cell transcriptomes are enriched for genes

involved in cell cycle, metabolism, and TNF-, IL-2/STAT5-, IFNg-, Notch-, and MTORC1-mediated

signaling pathways (**Fig. 1C**, **Table S1**).

To define global gene expression dynamics during the course of CD4+ T cell activation, we

performed pairwise comparisons and k-means clustering across the three cell states assayed.

This approach identified 4390 differentially expressed genes after 8 hours of stimulation (3289

upregulated and 1101 downregulated) and 3611 differentially expressed genes between 8 hours

and 24 hours (3015 upregulated and 596 downregulated, **Fig. S1D**) that could be further

separated into five clusters based on their distinct trajectories: upregulated early (cluster 1;

n=1621 genes), downregulated late (cluster 2; n=1600 genes), monotonically increasing (cluster

3; n=2676 genes), downregulated early (cluster 4; n=1628 genes) and upregulated late (cluster

5; n=2154 genes, **Fig. 1D**, **Fig. S1E-G**, **Table S2**).

Genes upregulated early (cluster 1; *e.g.*, *IL2, IFNG, TNF, IL3, IL8, IL2RA, IL15RA, IL21R,*

ICOS, CD40LG, FASLG, MYC, FOS, FOSB, FOSL1, FOSL2, JUNB, REL, NFKBID, NFKB1,

RELB, NFKBIA, STAT5A, BATF, BTLA) are enriched for pathways involved in the unfolded

protein response, cytokine signaling, and translation (**Fig 1E**; **Table S3**), and genes

downregulated late (cluster 2) are moderately enriched for receptor tyrosine kinase signaling,

cytokine signaling, and extracellular matrix organization. Genes monotonically increasing upon

activation (cluster 3; *e.g.*, *TBX21, BHLHE40, LTA, IL12RB2, STAT1, SLAMF7, CCND2, CDK4,*

PRMT1, ICAM1, NFKB2, EZH2) are highly enriched for pathways involved in infectious disease

and RNA stability, translation and metabolism, and moderately enriched for pathways involved in

the unfolded protein response, cellular responses to stress, regulation of apoptosis, and DNA

repair. Genes downregulated early upon stimulation (cluster 4; *e.g.*, *KLF2, IL7R, NOG, PIK3IP1,*

TSC22D3, RORA, IL10RA) are enriched for pathways involved in inositol phosphate biosynthesis,

neutrophil degranulation, and metabolism of nucleotides, and genes upregulated late (cluster 5;

e.g., *CDK2, E2F1, CDK1, CCNE1, CCNA2, PCNA, WEE1, CDC6, ORC1, MCM2*) are highly

enriched for pathways involved in cell cycle, DNA unwinding, DNA repair, chromosomal

maintenance, beta-oxidation of octanoyl-CoA, and cellular response to stress (**Fig 1E**; **Table S3**).

These patterns are consistent with known changes in the cellular processes that operate during

T cell activation, confirming that *in vitro* stimulation of CD4+ T cells recapitulates gene expression

programs known to be engaged during a T cell immune response.

Dynamic changes in chromosomal architecture and genome accessibility during naïve

CD4+ T cell activation

To understand the *cis*-regulatory dynamics underlying the observed activation-induced

changes in gene expression, we examined CD4+ T cell nuclear chromosome conformation and

chromatin accessibility as a function of stimulation state using HiC and ATAC-seq. The human

genome consists of ~3 meters of DNA that is incorporated into chromatin and compacted into the

~500 cubic micron nucleus of a cell in a hierarchically ordered manner. This degree of compaction

results in only ~1% of genomic DNA being accessible to the machinery that regulates gene

transcription[23], therefore a map of open chromatin regions (OCR) in a cell represents its potential

gene regulatory landscape. Open chromatin mapping of human CD4+ T cells at all states

identified a consensus *cis*-regulatory landscape of 181,093 reproducible OCR (**Table S4**). Of

these, 14% (25,291) exhibited differential accessibility following 8 hours of stimulation

(FDR<0.05). Most differentially accessible regions (DAR) became more open (18,887), but some

DAR (6,629) showed reduced accessibility (**Fig. 2A**, **Table S5**). The change in accessibility over

the next 16 hours of stimulation showed the opposite dynamic, with 6,629 regions exhibiting

reduced accessibility, and only 4,417 DAR becoming more open (total of 11,046 DAR, **Fig. 2A**,

Table S5). These OCR represent the set of putative cRE with dynamic activity during T cell

activation.

The vast majority of putative cRE are located in intergenic or intronic regions of the genome

far from gene promoters, meaning that the specific impact of a given cRE on gene expression

cannot be properly interpreted from a one-dimensional map of genomic or epigenomic features.

To predict which cRE may regulate which genes in CD4+ T cells across different states of

activation, we created three-dimensional maps of cRE-gene proximity in the context of genome

structure. The highest order of 3D nuclear genome structure is represented by A/B compartments,

which are large chromosomal domains that self-associate into transcriptionally active (A) *vs*.

inactive (B) regions[24]. In agreement with prior studies, we find that OCR located in active A

compartments exhibit higher average accessibility than those OCR located in less active B

compartments (**Fig S2A; Table S6**), a trend observed across all cell states. Likewise, genes

located in A compartments show higher average expression than those located in B

compartments (**Fig S2B**). A quantitative comparison across cell states showed that 94% of the

CD4+ T cell genome remained stably compartmentalized into A (42%) and B (52%), indicating

that activation does not cause a major shift in the large-scale organization of the genome within

the nucleus. However, ~6% of the CD4+ T cell genome did experience a transient (A>B>A or

B>A>B) or stable (A>B>B, A>A>B, B>B>A or B>A>A) shift in A/B compartmentalization in

response to activation (**Fig. 2B**). Genes that switched from A to B compartments are enriched for

processes involved in fatty acid receptors and metabolism, eicosanoid and leukotriene

biosynthesis, Runx and Yap activity, and IL-20 signaling, while genes that switched from B to A

compartments are enriched for pathways involved in cell-ECM and cell-cell interactions, vitamin

metabolism, and MECP2 activity (**Fig. 2B**), and include activation-induced genes known to

regulate T cell function like *EGR2* and *IL12RB2*.

Within each A or B compartment, the genome is further organized into topologically

associating domains (TADs)[25]. These structures are defined by the fact that genomic regions

within them have the potential to interact with each other in 3D, but have low potential to interact

with regions outside the TAD. The location of TAD boundaries can influence gene expression by

limiting the access of cRE to specific, topologically associated genes. While ~80% of TAD

boundaries remained stable across all states, 20% of TAD boundaries (8925) changed as a

function of T cell activation (**Fig. 2C**, **Fig. S2C** and **D**, **Table S7**). TAD boundary dynamics were

categorized and 2198 boundaries exhibited a change in strength, 2030 boundaries shifted

position, and 4697 boundaries exhibited more complex changes such as loss of a boundary

resulting in merger of two neighboring TAD, addition of a boundary splitting one TAD into two, or

a combination of any of these changes. Genes nearby dynamic TAD boundaries are enriched for

pathways involved in RNA metabolism, cellular response to stress, and the activity of PTEN, p53,

JAK/STAT, Runx and Hedgehog (**Fig. 2C**).

We detected chromatin stripes, which are TAD-like structures that consist of a genomic anchor

region that is brought into contact with a larger loop domain via an active extrusion mechanism.

Chromatin stripes are contained within and/or overlap TAD regions, and are enriched for active

enhancers and super-enhancers[26,27]. We identified 1526 chromatin stripes in quiescent naïve

CD4+ T cells, 1676 stripes in 8 hour stimulated cells, and 2028 stripes at 24 hours post-stimulation

(**Fig S3A**). Consistent with prior studies in other cell types, chromatin stripes were preferentially

located in A compartments, and genes and OCR within stripe regions showed increased

expression and chromatin accessibility (**Fig. S3B-D**).

Within active topological structures, transcriptional enhancers can regulate the expression of

distant genes by looping to physically interact with gene promoters[28,29]. To identify potential

regulatory cRE-gene interactions, we identified high confidence loop contacts across all cell states

using Fit-HiC (merged 1kb, 2kb, and 4kb resolutions, **Fig. 2D**). This approach detected 933,755

loop contacts in quiescent naïve CD4+ T cells, 900,267 loop contacts in 8-hour stimulated cells,

and 551,802 contacts in 24-hour stimulated cells (2,099,627 total unique loops). Approximately

23% of these loops involved a gene promoter at one end and an OCR at the other, and these

promoter-interacting OCR were enriched for enhancer signatures based on flanking histone

marks from CD4+ T cells in the epigenome roadmap database[30] (**Fig. S2E**). T cell activation

resulted in significant reorganization of the open chromatin-promoter interactome, as 907

promoter-OCR exhibited increased contact and 1333 showed decreased contact following 8

hours of stimulation (**Fig. 2E**). Continued stimulation over the next 16 hours was associated with

an increase in the contact frequency of 41 promoter-OCR pairs, while only 4 pairs exhibited

decreased contact (**Fig. 2E**). Activation-induced changes in chromatin architecture and gene

expression were highly correlated, as genomic regions exhibiting increased promoter connectivity

became more accessible at early stages of stimulation, which was associated with increased gene

transcription from connected promoters (**Fig. 2F, Table S8**). The accessibility of promoter-

connected OCR and the expression of their associated genes decreased globally from 8 to 24

hours of stimulation (**Fig. 2F**). We compared these loop calls to a prior chromatin capture analysis

in CD4+ T cells by Burren et al.[17] and found that roughly 40% of stable loops in both stimulated

and unstimulated cells were identical in both studies, despite differing in approach (HiC vs.

PCHiC), analysis (HiC vs. CHiCAGO), sample (naïve CD4+ vs. total CD4+), timepoint (8 vs. 4

hour), and donor individuals (**Fig. S2F**). As expected, unstimulated samples were more similar

than activated samples.

We next focused on the 5 sets of genes with the dynamic expression patterns defined in **Fig.**

1D, and identified 57,609 OCR that contact dynamic gene promoters in at least one stage. Most

dynamic genes contacted between 1 and ~35 OCR, with a median of 10 OCR per gene, but a

handful of dynamic genes were observed in contact with over 100 distinct open chromatin regions

(**Fig. S2G**). Similarly, most OCR were connected to a single dynamic gene, but many contacted

more than one gene (median 2 genes per OCR), suggesting that most dynamic genes have a

complex regulatory architecture. Increased gene expression upon activation correlated with an

increase in the accessibility and promoter contact frequency of distant cRE (**Fig**. **S2H**), as

exemplified by *GEM* and *IRF4* (**Fig. S4A**,**B**). Conversely, the 3D regulatory architecture of genes

like KLF2 and DPEP2, which were downregulated following stimulation, exhibited decreased

contact and accessibility (**Fig. S4C**,**D**).

Transcription factor footprints enriched in dynamic open chromatin identify regulators of

T cell activation

To explore what factors drive dynamic changes in the regulatory architecture of the CD4+ T

cell genome during activation, we conducted a quantitative footprinting analysis at 1,173,159

transcription factor (TF) motifs located in the consensus CD4+ T cell open chromatin landscape

using the average accessibility of the region surrounding each motif as a measure of regulatory

activity (**Table S9**). Activation of naïve CD4+ T cells resulted in increased chromatin accessibility

around bZIP motifs at tens of thousands of genomic regions by 8 hours post-stimulation (**Fig. 3A**

and **C**, **Table S9**), which was associated with increased expression of Fos and Jun family

members constituting the AP-1 complex, as well as the bZIP factors BATF, BACH1, and BACH2

(**Fig. 3A**). The activity of NFE2 and SMAD was increased without increased expression (**Fig. 3A**

and **C**), likely due to post-translational regulation of these factors by phosphorylation[31].

Conversely, the motifs for a number of TF exhibited significantly reduced accessibility early after

stimulation, including those for EGR2 and FOXP3 that are known to negatively regulate T cell

activation[32,33] (**Fig. 3A**). By 24 hours post-activation, bZIP activity remained largely unchanged

compared to 8 hours (**Fig. 3B**), but a number of factors showed decreased activity. These include

several members of the Sp family, the Myc cofactor MAZ that also cooperates with CTCF to

regulate chromatin looping[34], KLF2, which controls genes involved in naïve CD4+ T cell

quiescence and homing[2,35], NRF1, a factor implicated in age-associated T cell hypofunction[36],

and EGR2 and 3, which are known to oppose T cell activation and promote tolerance[32,37,38] (**Fig.**

3B and **C**).

To explore how transcription factor activity may operate *via* the CD4+ T cell open chromatin

landscape to regulate distinct programs of dynamic gene expression during TCR/CD28-induced

activation, we focused on TF motifs enriched among those OCR specifically contacting promoters

of dynamic genes identified by our clustering analysis (**Fig. S5A**). The set of OCR contacting

dynamic gene promoters were enriched for the motifs of 89 expressed (TPM>5) transcription

factors, as compared to motifs present in the total open chromatin landscape (**Fig. 3D**). The

majority of this TF activity was enriched in OCR connected to genes highly upregulated at 24

hours post-activation (clusters 3 and 5, **Fig. 3D**), with the exception of CREB3, ELF1, ESRRA,

GABPA, RELA, XPB1, ZNF384, and the transcriptional repressor IKZF1 known as a strong

negative regulator of T cell activation and differentiation[39–42]. Conversely, motifs for IKZF1,

ZNF384, GABPA, ESRRA, and ELF1 were highly enriched in the set of OCR contacting genes

down-regulated early after activation (cluster 4, **Fig. 3D**). Motifs for KLF2 and the metabolic gene

regulator SREBF1 were likewise enriched in OCR connected to down-regulated genes. Open

chromatin regions interacting with genes in cluster 2 are negatively enriched for this set of TF

except for CTCF (**Fig. 3D**).

Finally, we integrated TF footprint, promoter connectome, and gene co-expression data to

construct TF-gene regulatory networks likely operating at each timepoint. The connections

between regulatory nodes are based on physical promoter-TF footprint interactions with

confidence weighted by gene co-expression (**Fig. 3E**, **Table S10**). Highly co-expressed genes at

the core of the unstimulated CD4+ T cell regulatory network encode transcription factors such as

KLF2, ETS1, IKZF1, and TCF7[43–45] that are known to be involved in T cell gene silencing,

quiescence, homeostasis, and homing. Genes connected to the top factors in this network were

enriched for pathways involved in immune signaling, DNA replication and repair, protein secretion,

and programmed cell death (**Fig S5B**). Costimulation through the TCR and CD28 induced a set

of core network genes active at both time points with known roles in T cell activation and

differentiation (*NFKB1, JUNB, MYC, IRF4, STAT5, STAT1, LEF1, ATF4*). Also part of this set is

PLAGL2, an oncogene in the Wnt pathway that regulates hypoxia-induced genes[46] with no prior

defined role in T cell activation. Additional nodes specifically implicated at 8 hours post-activation

are HIF1A, the major sensor of cellular hypoxia[47], and XBP1, a major transcriptional mediator of

the unfolded ER protein response with defined roles in T cell activation, differentiation, and

exhaustion[48,49]. Factors specifically implicated at 24 hours post-activation include E2F1, a

transcriptional regulator of both cell cycle and apoptosis in T cells[50,51], BHLHE40, a factor known

to control multiple aspects of T cell metabolism and differentiation[52], and the Myc cofactor MAZ

that has not been previously studied in the context of T cell function. Genes connected to factors

in the activated T cell networks were enriched for pathways involved in cytokine signaling, the

interferon response, transcription, cell cycle, DNA replication and repair, and programmed cell

death (**Fig S5B**). Together, these data indicate that concurrent but separable stimulation-induced

gene programs are the result of the activity of distinct sets of DNA binding factors mobilized by

antigen and costimulatory receptor signaling in naïve CD4+ T cells.

Identification of autoimmune variants associated with CD4+ T cell cREs and putative

effector genes

Following our established variant-to-gene (V2G) mapping approach to implicate functional

SNPs and their effector genes using the combination of GWAS and chromatin conformation

capture data[53–57], we intersected promoter-interacting OCR with autoimmune SNPs from the 95%

credible set derived from 15 autoimmune diseases (**Fig. 4A**, **Tables S11** and **S12**). Constraining

the GWAS SNPs in this way reduced the credible set size from an average of 14 variants per

sentinel to 3 variants per sentinel. To determine whether open chromatin in physical contact with

dynamically regulated genes in CD4+ T cells is enriched for autoimmune disease heritability, we

performed a partitioned LD score regression analysis. This landscape was enriched for variants

associated with susceptibility to inflammatory bowel disease (IBD), ulcerative colitis (UC), type I

diabetes (T1D), lupus (SLE), celiac disease (CEL), allergy (ALG), eczema (ECZ), and rheumatoid

arthritis (RA), but not for variants associated with psoriasis (PSO) or juvenile idiopathic arthritis

(JIA) (**Fig. 4B**, **Table S13**). The OCR connected to genes upregulated early and/or progressively

upon activation (clusters 1 and 3) were most strongly enriched for ALG, CEL, IBD/UC, RA and

T1D heritability, while SLE and ECZ heritability was most enriched in OCR connected to genes

upregulated later post-activation (clusters 3 and 5, **Fig. 4B**). SLE was also the only disease

(besides PSO and JIA) that was not enriched in open chromatin connected to down-regulated

genes (cluster 4, **Fig. 4B**).

The promoter-connected open chromatin landscape for all CD4+ T cell states in this study

contains 2606 putatively causal variants linked to ~half of the sentinel signals (423) for the 15

diseases analyzed, and are in contact with a total of 1836 genes (**Table S12**). A total of 1151

autoimmune variants localized to the promoters of 400 genes (-1500/+500bp from the TSS, **Table**

S14). These variants were on average 103 kb from the TSS of their connected gene (**Fig. 4C**),

and each variant contacted an average of 5 genes (**Fig. 4D**). The majority of contacted SNPs

interact with genes in addition to the nearest gene, and ~half of linked SNPs 'skip' the nearest

gene to target only distant genes (**Fig. 4E**). Approximately 60% of connected genes were

implicated across all timepoints (**Fig. 4F**, **Table S12**), while ~40% (753) are dynamically regulated

(clusters 1-5) in response to TCR/CD28 co-stimulation. Examples of SNP-genes pairs that exhibit

dynamic accessibility, chromosome contact, and expression in response to T cell activation are

the *SIK1*, *PARK7*, *DUSP5*, *CLEC2D*, *TRIP10*, *GPR108* and *IL2* loci (**Fig. 4G**, **Table S12**). The

TRIP10 and *GPR108* promoters were each captured in contact with a high confidence variant

rs1077667 (PP>0.99), which is located in an intron of *TNFSF14* and is associated with multiple

sclerosis (**Fig. 4H**). The accessibility of this SNP and it's contact with *TRIP10* and *GPR108*

increased following activation (**Fig. 4H**). Conversely, the allergy-associated SNP rs7380290 is

accessible and contacts the *SIK1* promoter in resting cells, but shows reduced accessibility and

promoter connectivity upon activation (**Fig. 4I**). *TRIP10* encodes a cytoskeletal binding protein

involved in endocytosis that suppresses glucose uptake in response to insulin signaling[58],

GPR108 encodes an orphan G-protein coupled receptor, and *SIK1* encodes a salt-inducible

kinase with roles in cancer, epilepsy, and myeloid signaling[59]. None of these genes have been

previously implicated in T cell activation.

Functional validation of autoimmune V2G-implicated cis-regulatory elements

This analysis specifically implicated potential dynamic, disease-associated regulatory

elements in intergenic space at the *IL2* locus. The *IL2* gene encodes a cytokine with crucial,

pleotropic roles in the immune system, and dysregulation of IL-2 and IL-2 receptor signaling leads

to immunodeficiency and autoimmune disorders in mice and humans[60–63]. Activation-induced

transcription of *IL2* involves an upstream regulatory region (URR) ~375 bp from the TSS that has

served as a paradigm of tissue-specific, inducible gene transcription for nearly four decades[64–66].

However, the presence of evolutionarily conserved non-coding sequences (CNS) in the ~150 kb

of intergenic space 46, 51, 80, 83, 85, 96, 122, and 128 kb upstream of the TSS suggest that

additional regulatory elements may have evolved to control *IL2*[67] (**Fig. 5A**). The -51 kb CNS

contains a SNP linked to T1D, IBD, PSO, CEL and allergy (rs72669153), while the -85 kb CNS

contains a SNP linked to RA (rs6232750) and the -128 kb CNS contains two SNPs linked to T1D,

JIA, and SLE (rs1512973 and rs12504008, **Fig. 5A**). In TCR/CD28-stimulated naïve CD4+ T cells,

these CNS are remodeled to become highly accessible (**Fig. 5A**), and they loop to interact

physically with the *IL2* URR (**Fig. 5B**) at both time points. ChIP-seq analyses in human T cells

(ENCODE[68]) show that the URR and all distal CNS except -85 are occupied by TF such as

Jun/Fos (AP-1), NFAT, and NFkB that are known regulators of *IL2* (**Fig. S6**), and the -85, -122,

and -128 CNS are occupied by additional TF not previously thought to be direct regulators of *IL2*,

such as MYC, BCL6, and STAT5 (**Fig. S6**). Recombinant reporter assays in primary activated

human CD4+ T cells showed that the -46, -51, -83, and -128 CNS/OCR can enhance transcription

from the URR (**Fig. 5C**). To determine whether the native elements contribute to the expression

of *IL2*, we targeted each CNS/OCR individually in primary human CD4+ T cells or Jurkat T cells

using CRISPR/CAS9 (**Fig. 5D**) and measured IL-2 secretion following TCR/CD28 stimulation

(**Fig. 5E**). Deletion of the -46, -51, -83, -85, -122, and -128 kb elements in primary human CD4+

T cells each resulted in a ~50% reduction in IL-2 production, while deletion of the -80 kb element

had little effect. A very similar pattern of impact was observed when these elements were deleted

individually in Jurkat T cells (**Fig. 5E**). The URR has a stronger contribution to IL-2 production

than any individual intergenic element, as deletion of the URR almost completely abrogated

activation-induced IL-2 production by both primary CD4+ or Jurkat T cells (**Fig. 5E**). To determine

whether these intergenic enhancers exist in synergistic epistasis[69] necessary for *IL2*

transactivation, we generated Jurkat T cell clones in which the stretch of all 7 elements located -

46 kb to -128 kb upstream of *IL2* was deleted using CRISPR/CAS9 (**Fig. 5F**). Despite the URR

and 46 kb of upstream sequence being intact in these clones, loss of the 81.3 kb stretch of

intergenic enhancers renders these cells incapable of expressing *IL2* at both the mRNA and

protein level in response to stimulation (**Fig. 5G**). These results show that the URR is not sufficient

for activation-induced expression of *IL2*, and that *IL2* has a previously unappreciated, complex,

and autoimmune disease-associated regulatory architecture that was accurately predicted by our

3D epigenomic V2G approach. Importantly, we find that the distal *IL2* cRE are highly accessible

in quiescent memory T cell subsets (Th1, Th2, Th17, Th1-17, Th22) isolated directly *ex vivo* from

human blood, whereas naïve CD4+ T cells and non-IL-2-producing Treg showed little accessibility

at these elements (**Fig. S6**). This suggests that stable remodeling of distal *IL2* cRE can persist *in*

vivo after TCR signals cease, and that this epigenetic imprinting contributes to the immediate,

activation-induced production of IL-2 exhibited by memory, but not naïve or regulatory, CD4+ T

cells[70–72].

Impact of autoimmune risk-associated genetic variation on *cis*-regulatory element activity

The chromatin conformation approach used here employs GWAS variants as 'signposts' to

identify disease-relevant regulatory elements and connect them to their target genes, but does

not *per se* determine the effect of disease-associated genetic variation on enhancer activity or

gene expression. Expression quantitative trait loci (eQTL) studies identify variant-gene pairs

through statistical associations between gene expression and genotype, offering an orthogonal

line of evidence to compare with chromatin conformation capture approaches that identify variant-

gene pairs by biophysical association. We compared our variant-gene pairs to those from a recent

scRNA-seq-based eQTL study in activated CD4+ T cells[13] and identified 41 (out of 127) pairs

implicated by both methods, an overlap 10-fold higher than obtained by random sampling of

genes within 500 kb of autoimmune variants (**Fig. 6A, Fig S7A**). We experimentally validated

variant effects at the *IL2* locus, where the -128 enhancer defined above contains two SNPs linked

to T1D, JIA, and SLE (rs1512973 and rs12504008). Using a recombinant reporter assay in

primary activated CD4+ T cells, we confirmed that disease-associated genetic variation influences

intergenic *IL2* enhancer activity at the -128 kb element, in that the risk allele contributes

significantly less transcriptional activity than the reference allele (**Fig. 5H**).

Autoimmune variants are likely to influence disease risk by altering the activity of *cis*-

regulatory elements in T cells. Indeed, we identified over 1000 cRE likely impacted by

autoimmune disease-associated genetic variation, in that they contain autoimmune risk SNPs

that are predicted to decrease or increase transcription factor binding affinity. Overall, 1370

autoimmune risk variants in open chromatin were predicted to influence the activity of 495 DNA

binding factors (**Table S15**), including PLAG1, PRDM1, BACH2, MYC, TBX21, BHLHE40, LEF1,

TCF7, BCL6, IRF, p53, STAT (**Fig. S8A**), and hundreds of NFkB, EGR, KLF, FKH/FOX, and FOS-

JUN sites (**Fig. 6B**). For example, the MS-associated SNP rs1077667 is located in an element

that exhibits increased accessibility and contact frequency with the promoters of *GPR108* and

TRIP10 upon activation. This variant was predicted to reduce affinity for TP53, TP63, and

OCT2/POU2F2 (**Fig. S8B**). Similarly, the T1D SNP rs3024505 (PP = 0.200) connected to the

promoters of *IL9* and *FAIM3* (**Fig. S8C**) was predicted to disrupt binding of *MZF1*, while the celiac

SNP rs13010713 (PP = 0.154) contacting the *ITGA4* promoter (**Fig. S8D**) likely disrupts a SOX4

binding site.

Functional validation of V2G-implicated effector gene sets

To determine whether genes identified *via* their physical interaction with autoimmune variants

in CD4+ T cell chromatin contact maps tend to be directly involved in T cell activation and function,

we compared the set of autoimmune genes implicated by chromatin contacts in this study to sets

of genes identified in CRISPR-based screens that control aspects of CD4+ T cell activation like

proliferation and expression of the inflammatory genes *IFNG, CTLA4, IL2, IL2RA,* and *TNF*[20–22].

The set of all V2G-implicated genes was highly enriched for genes shown to regulate IL-2, IL-2

receptor, CTLA-4, and proliferation (**Fig. 6C, Fig. S7B, Table S16**). For example, 202 genes

shown to regulate IL-2 production and 166 genes shown to regulate proliferation were also

implicated in our autoimmune V2G set (**Table S16**). Genes implicated by V2G in activated CD4+

T cells were moderately enriched for genes known to control the production of IFN-G, but at the

individual disease level, only genes connected to CRO- and ATD-associated variants were

enriched for IFNG regulatory genes (**Fig. 6C, Fig. S7B**). Genes contacting CRO, PSO, RA, SLE,

T1D and VIT variants were moderately enriched for TNF regulatory genes, but the set of all V2G

genes was not enriched for TNF genes. We also queried the orthologs of our V2G-implicated

genes from the international mouse phenotype consortium (IMPC) database and identified 97

genes that when knocked out give an immune phenotype and 126 V2G genes that result in a

hematopoietic phenotype (**Fig. 6D**, **Fig. S7C**, **Table S16**). This frequency of observed

immune/hematopoietic phenotypes represents a significant (adjP<0.05) ~30% enrichment over

expected. This gene set was also enriched for mortality, homeostasis/metabolism, growth/body

size, skeleton, and embryonic phenotypes (**Fig. 6D**, **Table S16**).

Identification of novel regulators of T cell activation

An important application of this V2G approach is the identification of novel regulators of T cell

activation and their potential as drug targets, as nearly 20% of implicated gene products have at

least one chemical modulator currently available (**Fig 6E**, **Table S17**). As shown above, this

approach validates genes that are well-studied regulators of T cell function, however, a significant

portion of implicated genes are not well-studied and are not currently known to regulate T cell

activation (**Fig. 6F**). We observed a trend that genes expressed more highly in immune tissues

(GTEX) have in general been better investigated, and identified several less-studied genes that

could encode novel targets, including the kinases GRK6, PTK6, SIK1, and MAP3K11, the G

protein-coupled receptors OXER1, GPR183, GPR18, and KISS1R, the acetylcholine receptor

CHRNB1, and the *de novo* purine pathway enzyme GART. To determine whether these V2G-

implicated genes are novel regulators of T cell activation, we used commercially available

pharmacologic modulators in dose-response assays of activation-induced T cell proliferation.

Stimulation of T cells in the presence of ligands for CHRNB1, KISS1R and OXER1 did not

significantly affect T cell proliferation, however, small molecules targeting GRK6, PTK6,

MAP3K11, GPR183, GART, and SIK1 inhibited activation of both human and mouse T cells in

the nanomolar to micromolar range (**Fig. 6G**). Together, these data show that maps of dynamic,

3D variant-gene chromatin contacts in stimulated CD4+ T cells are able to identify genes with

bona fide, evolutionarily conserved roles in T cell activation.

DISCUSSION

By measuring dynamic changes in chromosome folding, chromatin accessibility, and gene

expression in naïve CD4+ T cells as a function of TCR-CD28 costimulation, we identified the

putative *cis*-regulatory landscape of autoimmune disease-associated genetic variation, and

physically connected these elements to their putative effector genes. We conducted

pharmacologic targeting experiments and compared our results with orthogonal eQTL and

CRISPR-based studies to validate sets of effector genes with a confluence of evidence supporting

their role in CD4+ T cell activation. This study and prior studies show that most cRE and their

variants interact with, and therefore have the potential to regulate, more than one gene (median

5 in this study), and the majority of cRE/variants 'skip' the nearest gene to interact with distant

genes[54,73,74]. For these reasons, chromatin conformation mapping in disease-relevant cell types

brings a crucial added dimension to genome-scale 1D data for understanding the complex genetic

and epigenetic mechanisms that regulate gene expression, and for predicting novel therapeutic

targets.

Many of the genes identified in this 3D epigenomic V2G screen have known roles in T cell

activation and function. An example is *IL2*, and we used the resulting maps to identify and validate

a stretch of previously unknown distal enhancers whose activity is required for *IL2* expression and

is influenced by autoimmune genetic variation. Another example is the phosphatase DUSP5 that

regulates MAPK signaling during T cell activation[75,76]. However, roles for many of the genes

implicated here in T cell activation are not known. For example, one of the top implicated genes,

PARK7, is a deglycase studied in the context of Parkinson's disease, but has a recently been

shown to modulate regulatory T cell function[77]. The orphan G protein-coupled receptor GPR108

is another top gene in our study that has not been studied in T cells, but was identified in a recent

CRISPR screen for genes affecting IL-2 levels[22]. Also co-implicated by our study and recent

CRISPR screens are the cannabidiol receptor GPR18[78] and the purine biosynthetic enzyme

GART[79]. The GPR18 agonist arachidonyl glycine inhibited CD4+ T cell activation above 10 uM,

while the GPR18 antagonist O-1918 slightly enhanced T cell activation. Antagonism of GART, an

enzyme we previous identified as a V2G effector gene in COVID19 severity[56], with the FDA-

approved drug lometrexol inhibited T cell activation in the 10 nM range. Antagonism of GRK6, a

member of the G-coupled receptor kinase family associated with insulin secretion and T2D

susceptibility[80], and PTK6, an oncogenic kinase studied in the context of cancer[81], led to inhibition

of T cell activation in the nM to uM range. Inhibition of MAP3K11, a kinase that facilitates signaling

through JNK1 and IkappaB kinase in cancer[82,83], and 25-hydroxycholesterol, a ligand of the G

protein-coupled receptor GPR183, inhibited stimulation-induced CD4+ T cell proliferation in the

100 nM range. SIK1 is a member of the salt-inducible kinase family that negatively regulates

TORC activity[59], and a small molecule SIK1 inhibitor potently antagonized stimulation-induced

CD4+ T cell activation in the pM range.

Our integration of high-resolution Hi-C, ATAC-seq, RNA-seq and GWAS data in a single

immune cell type across multiple activation states identified hundreds of autoimmune variant-

gene pairs at ~half of all GWAS loci studied, and application of this technique to additional immune

cell types will likely identify effector genes at many of the remaining loci. This study highlights the

value of chromosome conformation data as a powerful biological constraint for focusing variant-

to-gene mapping efforts[84], and shows that dynamic changes in the spatial conformation of the

genome that accompany cell state transitions alter gene expression by exposing promoters to a

varying array of *cis*-regulatory elements, transcription factors, and genetic variants.

MATERIALS AND METHODS

<u>T cell isolation and *in vitro* stimulation</u>

Human primary CD4+ T cells were purified from the apheresis products obtained from healthy,

screened human donors through University of Pennsylvania Human Immunology Core (HIC).

Naïve CD4+ T cells were purified using EasySepTM Human naïve CD4+ T cell isolation kit II

(STEM cells Technologies, cat#17555) by immunomagnetic negative selection as per

manufacturer's protocol. Isolated untouched, highly purified (93-98%) naïve human CD4 T cells

were activated using anti-CD3+ anti-CD28 Dynabeads (1:1) (Thermofisher scientific, cat #

11161D) for 8-24 hours. Cells were then used to prepare sequencing libraries. The human

leukemic T cell line Jurkat was obtained from ATCC, cloned by limiting dilution, and clones with

high activation-induced secretion of IL-2 were selected for further study.

RNA-seq library generation and sequencing

RNA was isolated from ~ 1 million of each cell stage using Trizol Re- agent (Invitrogen), purified using the Directzol RNA Miniprep Kit (Zymo Research), and depleted of contaminating genomic DNA using DNAse I. Purified RNA was checked for quality on a Bioanlayzer 2100 using the Nano RNA Chip and samples with RIN>7 were used for RNA-seq library preparation. RNA samples were depleted of rRNA using QIAseq Fastselect RNA removal kit (Qiagen). Samples were then processed for the preparation of libraries using the SMARTer Stranded Total RNA Sample Prep Kit (Takara Bio USA) according to the manufacturer's instructions. Briefly, the purified first-strand cDNA is amplified into RNA-seq libraries using SeqAmp DNA Polymerase and the Forward and the Reverse PCR Primers from the Illumina Indexing Primer Set HT for Illumina. Quality and quantity of the libraries was assessed using the Agilent 2100 Bioanalyzer system and Qubit fluorometer (Life Technologies). Sequencing was performed on the NovaSeq 6000 platform at the CHOP Center for Spatial and Functional Genomics.

ATAC-seq library generation and sequencing

A total of 50,000 to 100,000 cells were centrifuged at 550 g for 5 min at 4 °C. The cell pellet was washed with cold PBS and resuspended in 50 µL cold lysis buffer (10 mM Tris-HCl, pH 7.4, 10 mM NaCl, 3 mM MgCl2, 0.1% NP-40/IGEPAL CA-630) and immediately centrifuged at 550 g for 10 min at 4 °C. Nuclei were resuspended in the Nextera transposition reaction mix (25 µL 2x TD Buffer, 2.5 µL Nextera Tn5 transposase (Illumina Cat #FC-121-1030), and 22.5 µL nuclease free H2O) on ice, then incubated for 45 min at 37 °C. The tagmented DNA was then purified using the Qiagen MinElute kit eluted with 10.5 µL Elution Buffer (EB). Ten microliters of purified tagmented DNA was PCR amplified using Nextera primers for 12 cycles to generate each library. PCR reaction was subsequently cleaned up using 1.5x AMPureXP beads (Agencourt), and

concentrations were measured by Qubit. Libraries were paired-end sequenced on the Illumina

HiSeq 4000 platform (100 bp read length).

Hi-C library preparation

Hi-C library preparation was performed using the Arima-HiC kit (Arima Genomics Inc), according

to the manufacturer's protocols. Briefly, cells were crosslinked using formaldehyde. Crosslinked

cells were then subject to the Arima-HiC protocol, which utilizes multiple restriction enzymes to

digest chromatin. Arima-HiC sequencing libraries were prepared by first shearing purified

proximally-ligated DNA and then size-selecting 200-600 bp DNA fragments using AmpureXP

beads (Beckman Coulter). The size-selected fragments were then enriched using Enrichment

Beads (provided in the Arima-HiC kit), and then converted into Illumina-compatible sequencing

libraries with the Swift Accel-NGS 2SPlus DNA Library Kit (Swift, 21024) and Swift 2S Indexing

Kit (Swift, 26148). The purified, PCR-amplified DNA underwent standard QC (qPCR, Bioanalyzer,

and KAPA Library Quantification [Roche, KK4824]) and was sequenced with unique single

indexes on the Illumina NovaSeq 6000 Sequencing System using 200 bp reads.

ATAC-seq data analysis

ATAC-seq   peaks   were   called   using   the   ENCODE   ATAC-seq   pipeline

(https://www.encodeproject.org/atac-seq/). Briefly, pair-end reads from three biological replicates

for each cell type were aligned to hg19 genome using bowtie2[85], and duplicate reads were

removed from the alignment. Narrow peaks were called independently for each replicate using

macs2[86] (-p 0.01 --nomodel --shift -75 --extsize 150 -B --SPMR --keep-dup all --call-summits) and

ENCODE blacklist regions (ENCSR636HFF) were removed from peaks in individual replicates.

Reproducible peaks, peaks called in at least two replicates, were used to generate a consensus

peakset. Signal peaks were normalized using csaw[87] in 10kb bins background regions and low

abundance peaks (CPM>1) were excluded from the analysis. Tests for differential accessibility

was conducted with the glmQLFit approach implemented in edgeR[88] using the normalization

factors calculated by csaw. OCRs with FDR < 0.05 and abs($\log_2$FC > 1) between stages were

considered differentially accessible.

<u>Hi-C data analysis</u>

Paired-end reads from two replicates were pre-processed using the HICUP pipeline v0.7.4[89], with

bowtie as aligner and hg19 as the reference genome. The alignment .bam file were parsed to

.pairs format using pairtools v0.3.0 (https://github.com/open2c/pairtools) and pairix v0.3.7

(https://github.com/4dn-dcic/pairix), and eventually converted to pre-binned Hi-C matrix in .cool

format by cooler v0.8.10[90] with multiple resolutions (500bp, 1kbp, 2kbp, 2.5kbp, 4kbp, 5kbp,

10kbp, 25kbp, 40kbp, 50kbp, 100kbp, 250kbp, 500kbp, 1Mbp and 2.5Mbp) and normalized with

ICE method[91]. Replicate similarity was determined by HiCRep v1.12.2[90] at 10K resolution. For

each sample, eigenvectors were determined from an ICE balanced Hi-C matrix with 40kb

resolution using cooltools v0.3.2[92] and first principal components were used to determine A/B

compartments with GC% of genome region as reference track to determine the sign. Differential

TAD comparison was performed using TADcompare with the default settings for each

chromosome (v1.4.0)[93]. Finally, for each cell type, significant intra-chromosomal interaction loops

were determined under multiple resolutions (1kb, 2kb and 4kb) using the Hi-C loop caller Fit-Hi-

C2 v2.0.7[94] (FDR<1e-6) on merged replicates matrix. The consensus chromatin loops within

resolution were identified by combining all three stages. These sets of loops were used as

consensus for quantitative differential analysis explained below. The final consensus interaction

loops for visualization were collected by merging loops from all the resolutions with preference to

keep the highest resolution. Quantitative loop differential analysis across cell types was performed

on fast lasso normalized interaction frequency (IF) implemented in multiCompareHiC v1.8.0[95] for

each chromosome at resolution 1kb, 2kb and 4kb independently. The contacts with zero

interaction frequency (IF) among more than 80% of the samples and average IF less than 5 were

excluded from differential analysis. The QLF test based on a generalized linear model was

performed in cell type-pairwise comparisons, and p-values were corrected with FDR. The final

differential loops were identified by overlapping differential IF contacts with consensus interaction

loops.

<u>Bulk RNA-seq data analysis</u>

Bulk RNA-seq libraries were sequenced on an Illumina Novaseq 6000 instrument. The pair-end

fastq files were mapped to the genome assembly hg19 by STAR (v2.6.0c) independently for each

replicate. The GencodeV19 annotation was used for gene feature annotation and the raw read

count for gene feature was calculated by htseq-count (v0.6.1)[96] with parameter settings -f bam -r

pos -s yes -t exon -m union. The gene features localized on chrM or annotated as rRNAs, small

coding RNA, or pseudo genes were removed from the final sample-by-gene read count matrix.

Gene set variation analysis was performed using GSVA 1.42.0[97] with the MSigDB hallmark

geneset[98], with resulting scores analyzed using limma (limma_3.50.3)[99]. Low abundance peaks

(CPM>1) were excluded from the analysis. Testing for differential expression was conducted with

the glmQLFit approach implemented in edgeR[88]. Genes with FDR<0.05 and abs($\log_2$FC>1)

between stages were considered differentially expressed. Differential genes were then clustered

using k-means clustering. The number of clusters was determined using the elbow method on

the weighted sum of squares, where was set to k=5. Score for how similar each gene followed

the clusters expression pattern was determined by calculating pearson correlation coefficients

between each gene in the cluster and the cluster centroid.

<u>Transcription factor footprinting and motif analysis</u>

Transcription factor footprints were called using Regulatory Analysis Toolbox HINT-ATAC

(v0.13.0) with pooled ATAC-seq data for each stage and consensus peak calls[100]. The rgt-hint

footprinting was run with parameters –atac-seq, --paired-end, and organism=hg19 set. The output

footprint coordinates were subsequently matched using rgt-motifanalysis matching with

parameters --organism hg19 and –pseudocount 0.8 set. The JASPAR2020 position weight matrix

database was used to match footprints[101]. Differential analysis of TF binding across conditions

was performed using rgt-hint differential with parameters –organism hg19, --bc, --nc 24 using the

motif matched transcription factor footprints. An activity score is then calculated based on the

accessibility surrounding the footprint.

621
622 <u>Partitioned heritability LD score regression enrichment analysis</u>
623
Partitioned heritability LD score regression[102] (v1.0.0) was used to identify heritability enrichment

with GWAS summary statistics and open chromatin regions annotated to genes. The baseline

analysis was performed using LDSCORE data

(https://data.broadinstitute.org/alkesgroup/LDSCORE) with LD scores, regression weights, and

allele frequencies from the 1000G phase 1 data. The summary statistics were obtained from

studies as described in the supplemental table and harmonized with the munge_sumstats.py

script. Annotations for Partitioned LD score regression were generated using the coordinates of

open chromatin regions that contact gene promoters through Hi-C loops for each cell type. Finally,

partitioned LD scores were compared to baseline LD scores to measure enrichment fold change

and enrichment p-values, which were adjusted with FDR across all comparisons.

<u>Variant-to-gene mapping using HiC-derived promoter contacts</u>

95% credible sets were determined as previously described[103]. Briefly, P values from GWAS

summary statistics were converted to Bayes factors. Posterior probabilities were then calculated

for each variant. The variants were ordered from highest to lowest posterior probabilities added

to the credible set until the cumulative sum of posterior probabilities reached 95%. Variants in the

95% credible set were then intersected with the CD4+ T cell promoter interacting region OCRs

from the three timepoints using the R package GenomicRanges (v1.46.1)[104].

Genomic reference and visualizations

All analyses were performed using the hg19 reference genome using gencodeV19 as the gene reference. Genomic tracks were visualized with pyGenomeTracks v3.5[105]. HiC matrices depict the log1p(balanced count) from the cooler count matrix. ATAC-seq tracks were generated from bigwig files that were normalized using deeptools[106].

Colocalized eQTL comparisons

Enrichment of sentinel-gene assignments was conducted similarly as described previously[54]. Briefly, a null distribution was constructed by randomly selecting genes within 1 Mb of the sentinel compared to the set of colocalized cis-eQTL[13] found in through 10,000 iterations. The observed overlap reports the set of gene identified by both our HiC based approach with the set of colocalized eQTLs. We report the empirical P value of the observed value relative to null distribution.

International mouse phenotyping consortium comparisons

The set of HiC implicated genes were compared to the mouse international phenotyping consortium set of genes with reported phenotypes[107]. We converted the list of V2G implicated genes to mouse homologs using homologene. We tested for enrichment for each phenotype using a one-sided proportion test implicated in R prop.test with type set to "upper".

Identification of pharmacological agents

We queried the Drug-Gene Interaction Database with the set of V2G implicated genes for chemicals using rDGIdb (v1.20.0)[108]. To identify the number of papers for each gene with at least one drug annotated to target it, we queried pubmed titles and abstracts using the R package RISmed (v2.3.0) with each gene's name and either "autoimmune" and the list of autoimmune

diseases (**Table S17**). A score to approximate expression specificity was computed using the

sum GTEX median expression values (v8) for whole blood or spleen divided by other tissues[109].

Lentiviral-based CRISPR/CAS9 targeting in Jurkat cells

LentiCRISPRv2-mCherry vectors encoding gRNA-CAS9 and the fluorescent reporter mCherry

were used for Jurkat targeting. CRISPR guide RNAs (sgRNA) targeting human IL-2-21 intergenic

-46, -51, -80, -83, -85, -122, -128 CNS regions were designed using http://crispr.tefor.net and

cloned into lentiCRISPRv2-mCherry. Empty vector without gRNA insert was used as a control.

Below is the list of CRISPR gRNA for causing deletion of human IL2-21 intergenic regions:

CNS region   CRISPR gRNA

-46 CNS   gRNA #1   AGGATGCCTACCTCCAAATG

gRNA # 2 AGGTGACAACATTTAGTCAG

-51 CNS   gRNA #1   GGCAACGAAATTCACTGTGA

681   gRNA # 2 ATTCTAACAGGAATCATTCG

-80 CNS   gRNA # 1 GTTCTACCTATGCCGCATTG

gRNA # 2 GAGATTTACTCAGTCCAATG

-83 CNS   gRNA # 1 GTGACAAGCATGACTCTACA

gRNA # 2 GTGATGGTGAATTAAGCTGA

-85 CNS   gRNA #1   AGGGTTTTCTAGTTACGAGA

gRNA # 2 ATGGTTAGTTAGCTCCCAAG

-96 CNS   gRNA#1   TGGGAAAAACATCTTACCTG

gRNA # 2 TGGCCCATGAACCATCAAAG

-122 CNS   gRNA# 1   GTTATTAATCTAAGCGGAGA

gRNA# 2 GGAAGTTAGGCAGTCAATCG

-128 CNS   gRNA#1   CTTCAATCATTGCATTCCAC

gRNA# 2 TGACACCACCCCTGCTTGAG

HEK 293T cells were grown in RPMI1640 complete medium (RPMI1640 + 1X P/S, 1x L-Glu, 10%

FBS), 37C, 7%CO2. 293T cells were transfected with 10 ug of lenti-CRISPR-V2-CRE construct

along with packaging plasmid 6 ug of PsPAX2 (Addgene, Cat #12260) and 3.5 ug of PmD2.G

(Addgene, Cat #12259) using Lipofectamine 2000 transfection reagent (Invitrogen cat #

11668019). After 6 hours, the transfection medium was replaced with complete culture medium.

Transfected cells were incubated at 37C for 48-72 hours in a cell culture incubator. and then the

Lentiviral supernatants were harvested and spun at 300g for 5 minutes to remove cellular debris.

Lentiviral supernatants were concentrated using Lenti-X^{TM} Concentrator (Takara Bio, Cat #

631232) and then centrifuged at 1500g for 30 minutes at 4°C and supernatant was discarded.

The lentiviral pellet was resuspended at a ratio of 1:20 of the original volume using RPMI media

and concentrated virus supernatant aliquots were prepared and stored until use at -80°C. To

achieve high transduction efficiency, the viral supernatant was titrated in Jurkat cells through

transduction using various dilutions of the viral supernatants and transduction efficiency was

determined by mcherry expression analyzed through flow cytometry. Jurkat cells were seeded in

a 24 well plate at 0.5 x106/well in culture media, viral supernatant with 8 ug/mL of polybrene was

added to each well. Spinfection was performed for 90 min. at 2500 rpm, and transduced cells

were equilibrated at 37C for ~6 hrs, followed by incubation at 37C 5%CO2 for ~72 hours culture.

Transduced Jurkat Cells were then harvested and stimulated using PMA (15 ng/mL) + Ionomycin

(1 uM) + human anti-CD28 (2 ug/ml), BioXcell cat # BE0248 in 96 well culture plates (TPP, cat #

92097) in triplicates. Cell culture supernatants were collected at the end of culture and analyzed

for IL-2 by ELISA using a kit (cat # 88-7025-76) purchased from Thermofisher Scientific.

gRNA-CAS9 RNP-based targeting in primary human CD4+ T cells

Primary Human CD4 T cells derived from 5 normal healthy donors were obtained from Human

Immunology core (University of Pennsylvania). Alt-R S.p. HiFi Cas9 Nuclease V3 cat # 1081061

CAS9 and following list of Alt-R® CRISPR-Cas9 sgRNA targeting IL-2-21 CRE were purchased

from Integrated DNA Technologies, USA.

Name	20nt gRNA Seq
46CNS-1	GACGTATATAGTCATCTGAT
46CNS-2	TCTGTGGAGCTGCTGCGTTA
46CNS-3	AGGATGCCTACCTCCAAATG
51CNS-1	ATTCTAACAGGAATCATTCG
51CNS-2	GAGTAAAAAGACGTGTTACC
51CNS-3	GGCAACGAAATTCACTGTGA
80CNS-1	AATGCGGCATAGGTAGAACT
80CNS-2	GAGATTTACTCAGTCCAATG
80CNS-3	TGGTTGTCACAGTAACTAGG
83CNS-1	GTGACAAGCATGACTCTACA
83CNS-2	GTGATGGTGAATTAAGCTGA
83CNS-3	TGGGCTCTGACTCACTTAGA
85CNS-1	GCTAACATTGACTTCTCTAC
85CNS-2	AATCTATGCAAGGGGTGAAT
85CNS-3	GCATCATGATGAAGCTTATC
122CNS-1	GTTATTAATCTAAGCGGAGA
122CNS-2	GGAAGTTAGGCAGTCAATCG
122CNS-3	CACTTTGTGCTCGGATGCTC
128CNS-1	CTTCAATCATTGCATTCCAC
128CNS-2	TCAAGCAGGGGTGGTGTCAA
128CNS-3	TGGTGATTCATCTTTAGCAT
IL-2URR-1	TCCATTCAGTCAGTCTTTGG

IL-2URR-2	TAGTGTCCCAGGTGATTTAG
IL-2URR-3	TAGAGCTATCACCTAAGTGT
B2m-1	GAGTAGCGCGAGCACAGCTA
B2m-2	CACGCGTTTAATATAAGTGG

Primary Human CD4 T (5-10e6) were incubated with sgRNA and CAS9 protein complex and

electroporation was done using P3 Primary Cell 4D-Nucleofector™ X Kit L (Lonza, cat # V4XP-

3024) and Lonza 4D nucleofector system. B2M gene was CRISPR targeted as a positive control.

As per manufacturer's protocol cells were electroporated pulse code Fl-115 in 100ul cuvette

format. After nucleofection, cells were allowed to rest in the complete media for ~2 days. Cells

were then harvested, washed with PBS and aliquots of cells were used for further experimentation

such as flow staining and cell activation. Primary human CD4 T Cells (0.1e6/well) were seeded

in triplicates (for each experimental condition) in 96 well plate format in RPMI complete medium

and stimulated using ImmunoCult™ Human CD3/CD28 T Cell Activator (STEM cells

Technologies, cat # 10971). Cell culture supernatants were collected at 4h of stimulation and

stored at -80C until assayed. IL-2 ELISA was performed using Thermofisher Scientific IL-2 Human

Uncoated ELISA Kit with Plates, cat # 88-7025-76.

Recombinant reporter assays

The *IL2* URR was cloned into Xho I and Hind III sites of PGL4 Luc vector (Promega) and then

~500 bp individual sequence representing *IL2-IL21* intergenic CNS at -46, -51, -80, -83, -85, -128

were cloned upstream to IL-2 URR at the Xho I site of the pGL4 vector. Primary human CD4 T

cells obtained from 5 normal healthy donors were transfected with PGL4-cRE-URR constructs.

Briefly, primary human CD4 T cells were activated with anti-CD3+ anti-CD28 Dynabeads (1:1)

(Thermofisher scientific, cat # 11161D) + IL-2 overnight and then 1 million aliquots of cells

(triplicates) were electroporated using Nucleofector 2b, human T cell Nuclefactor kit (Lonza VPA

1002, program # T-020) with 2ug of PGL4 firefly vector constructs along with 0.2 ug of PGL4

Renilla vector; cells were allowed to rest ON in RPMI + IL-2 and then re-stimulated with plate-

bound anti-CD3+ anti-CD28 (2 ug/ml each) for 5 hrs. Dual luciferase assay was performed with

cell lysate prepared using Promega dual luciferase assay kit. Cell lysate was prepared in PLB as

per manufacturer's protocols and then firefly and renilla luciferase activities were analyzed by

spectramax ID5 (Molecular Devices). Firefly luciferase activity was normalized against the internal

control renilla luciferase activity.

<u>Pharmacologic validation of novel T cell activation regulatory genes</u>

The drugs lometrexol (GART antagonist), 25-hydroxycholesterol (GPR183 ligand), epinephrine &

norepinephrine (CHRNB agonists), and arachidonoyl glycine (GPR18 agonist) were purchased

from Sigma. The GPR18 antagonist O-1918 was purchased from ChemCruz. CEP1347

(MAP3K11 antagonist), kisspeptin 234 (KISSIR ligand) and the PTK6 antagonist tilfrinib were

purchased from Tocris. The GRK6 antagonist GRK-IN-1 was purchased from DC Chemicals. The

SIK1 antagonist HG-91-9-1 was purchased from Selleckchem. The OXER1 agonist 5-Oxo-ete

was purchased from Cayman chemicals. The drugs were dissolved in DMSO or ethanol as

suggested by the vendor and working stocking concentrations were prepared in RPMI1640

medium or PBS. The drug effect on T cell proliferation was assayed using murine lymphocytes

cultured under TCR and CD28 activation conditions. Spleen and lymph nodes were collected from

6-8 weeks old female C57BL/7 mice and single cell lymphocyte cell suspensions were prepared

in RPMI 1640 complete medium. 20 million lymphocytes were labeled with CFSE and re-

suspended in RPMI 1640 medium. Cells (0.5 million labeled cells/well) were loaded into 48 well

culture plate and activated with mouse anti-CD3 and anti-CD28 agonistic antibodies (1μg mL

each). Drugs at the indicated concentrations were added in the culture medium and both

untreated and drug treated cell cultures were incubated at 37°C for 72 hours in a cell culture

incubator. Cells were harvested after 3 days of culture, washed with PBS and then stained with

live-dead aqua dye. After washing with FACS buffer (PBS containing 2% FBS), cells were stained

with fluorochrome conjugated antibodies CD4-APC, CD8-PB, CD44-Percp Cy5.5 and CD25-

BV650. Stained cells were analyzed on a Beckman Coulter Cytoflex S flow cytometer. The

division profile of CD4+ CFSE+ T cells were gated on live populations. The flow data was

analyzed using Flowjo10 software and the number of divided CD4+ T cells were determined as

described previously[110].

FIGURE LEGENDS

Figure 1: Defined gene expression dynamics throughout activation of naïve CD4+ T cells.

(**A**) Diagram of study design: RNA-seq, ATAC-seq, and HiC libraries were prepared from sorted

CD4+CD62L^{hi}CD44^{lo} naïve T cells (donor N=3) prior to or following 8hr or 24hr stimulation with

anti-CD3/28 beads. cREs are classified to genes allowing for interrogation of the pattern of

expression, accessibility, and chromatin structure changes of autoimmune-associated variants.

(**B**) Heatmap showing normalized expression of known markers of T cell activation. (**C**) Gene set

variance analysis (GSVA, N=3) using log-transformed expression values to MSigDB Hallmark

gene set. Red indicates higher activity and blue indicates lower activity. (**D**) K-means clustering

of differentially expressed genes into five groups using the elbow and within-cluster-sum of

squares methods to select the number of clusters. The centroid of the cluster is depicted as a

black line, and members of the cluster are depicted as colored lines. Color indicates the Pearson's

correlation coefficient between the gene and the cluster centroid, with red indicating higher

correlation, and blue lower correlation. (**E**) Gene set enrichment for each cluster of differential

genes using the REACTOME pathway database. Enriched pathways associated with differentially

expressed genes in those regions. X-axis indicates ratio of observed pathway members

compared to those expected by chance, the Y-axis indicates the -log10(p-value) of enrichment

(hypergeometric test), and dot size corresponds to the absolute number of genes observed in the

pathway.

Figure 2: Chromatin accessibility and architecture changes across three stages of T cell

activation. (**A**) Volcano plots depicting the $\log_2$ change in accessibility in all reproducible OCRs

(present in 2 of the 3 replicates) compared to the $-\log_{10}$(FDR), significant points are indicated in

red (FDR < 0.05; abs($\log_2$FC) > 1). (**B**) Genomic regions were classified by membership in A vs.

B compartments at each time point. The pie chart depicts regions with differential A/B

compartment assignment in response to activation. Significantly enriched pathways of genes

located in variable A/B compartments are shown as bubble plots. Color indicates the pattern of

A/B compartment assignment across the three timepoints, and node size indicates the number of

genes in that pathway. (**C**) TAD structure was determined at each time point, and regions

exhibiting a shift, split/merge, change in strength, or more complex rearrangements are depicted

in the pie chart. Enriched pathways associated with differentially expressed genes in those

regions are shown. (**D**) Loop calls identified from HiC data for each timepoint called at three

resolutions (1kb, 2kb, 4kb bins). (**E**) Differential loop-calls called across all resolutions. (**F**) Density

plots of cRE accessibility and gene expression separated by whether contact frequency

increased, decreased, or remained stable from the transition from unstimulated to 8 hour

activation and 8 hour to 24 hour activation.

Figure 3: Transcription factors prediction potential regulators of chromatin status and

expression changes. Footprints were annotated to each TF motif by sequence matching to the

JASPAR motif database, and the average accessibility of the region surrounding each motif was

used as a measure of activity at each time point. Scatterplots depict the change in accessibility

for each TF motif (activity score) and $\log_2$FC of TF gene expression between unstimulated and 8

hour activation (**A**) or 8 hour and 24 hour activation (**B**). TF were classified as differentially

expressed (orange), differentially active (brown), both (red), or neither (grey). Dot size indicates

the number of predicted footprints occupied by each motif. (**C**) Average accessibility (normalized

by depth and motif number) in a 200bp window surrounding motif footprints for FOSL2::JUNB,

Smad2::Smad3, MAZ, and KLF2 from three timepoints (unstim: green; 8hr: blue; 24hr: red). (**D**)

Z-score of TF motif enrichment for cRE connected to the five clusters compared to all OCR.

Lighter color indicates higher specificity of enrichment for that TF cluster. (**E**) Connections

between different TFs based on physical interactions and predicted regulation-based co-

expression determined by GENIE3 for the three timepoints. Node color indicates expression

(TPM; darker = higher expression, lighter = lower expression), edge color reflects confidence in

the interaction called by GENIE3 (darker higher confidence).

Figure 4: Variant-to-gene mapping of autoimmune-associated loci implicates genetic

variants in the control of T cell activation. (**A**) Identification of genes in contact with open

chromatin regions harboring autoimmune-associated SNPs. Sentinel SNPs from 15 autoimmune

GWAS (**Table S11**) were used to identify the 95% credible set of proxy SNPs for each lead SNP.

SNP locations were integrated with ATAC-seq and HiC data to identify the 95% credible set of

accessible SNPs in physical contact with a gene promoter. Genes are further refined based on

expression dynamics over the time course of T cell activation. (**B**) Partitioned LD score regression

for autoimmune GWAS studies using the OCR in contact with the genes in the five clusters

defined by RNA-seq. Circle size = enrichment, color = significance, **FDR<0.01, ***FDR<0.001.

(**C**) Log distribution of the 1D distance between each proxy SNP and its interacting gene based

on 3D chromatin conformation (median=103 kbp). (**D**) Distribution of the number of genes

contacted by each accessible variant (median=5). (**E**) Fraction of open disease-associated

variants that interact with no gene promoters (grey), only with the nearest gene promoter (purple),

with the nearest gene and a distant gene(s) (orange), and with only a distant gene(s) (blue). (**F**)

Number of genes identified by variant-to-gene mapping at each time point. Black = shared in all

stages, blue = shared in two stages, red = specific to one stage. (**G**) Set of implicated proxy-genes

pairs that are both differentially expressed, display differential accessibility, and chromatin contact

across T cell activation. (**H**) Example MS variant rs1077667 (PP=1.0) exhibits increased

accessibility and contact with the promoters of the *GPR108* and *TRIP10* at 8 hours post activation,

which are increased in expression at this time point. (**I**) Example allergy variant rs7380290

interacts with the *SIK1* gene that is upregulated after activation.

Figure 5: Functional validation of autoimmune V2G-implicated cRE at the *IL2* locus. (A) The

combination of evolutionary conservation (blue), open chromatin (red), and autoimmune disease-

associated SNPs at the *IL2* locus identify putative cRE in quiescent vs. 8-hour activated naïve

CD4+ T cells. (**B**) Activation-dependent TAD/sub-TAD structure (heatmaps), chromatin

remodeling (grey) and promoter-OCR interactions (red) at the *IL2* locus. (**C**) Recombinant reporter

assay showing transcriptional activity of the *IL2* URR (+35 to -500 from the TSS) in activated

primary CD4+ T cells (N=5 donors) compared to a basal promoter (pGL4, left panel). The right

panel depicts transcriptional activity of the CNS regions indicated in **A** cloned upstream of the

URR. All regions except the -80 CNS show statistically significant activity relative to the URR

alone (N=5, P<0.05, line = median, box = 95/5% range). (**D**) Scheme of CRISPR/CAS9-based

deletion of individual *IL2* CNS using flanking gRNAs. (**E**) Activation-induced secretion of IL-2

protein by CRISPR-targeted primary CD4+ T cells (N=5 donors, left panel) or Jurkat cells (N=3

replicates, right panel) relative to untargeted control (CAS9, no gRNA) cells (****P<0.0001,

***P<0.001, **P<0.01, *P<0.05, line = median, box = 95/5% range). In primary cells, *B2M* gRNAs

served as an irrelevant targeted control. (**F**) Scheme of CRISPR/CAS9-based deletion of the 81.3

kb region containing all distal *IL2* cRE using flanking gRNAs in Jurkat cells. (**G**) Activation-induced

IL-2 protein (left panel) and mRNA (right panel) by control (black) vs. 81.3 kb deleted (red) Jurkat

cells (N=3 separate clones). (**H**) Recombinant reporter assay in activated primary CD4+ T cells

(N=5 donors) showing transcriptional activity of the reference vs. risk alleles of the *IL2* -128 cRE

relative to the URR alone (P<0.0001).

Figure 6: Functional validation of autoimmune V2G-implicated genes. (**A**) Physical variant-

gene associations (HiC) are highly enriched for statistical variant-gene associations (eQTL) in

activated CD4+ T cells. The histogram depicts the null distribution of shared variant-gene pairs

expected at random (~5) while the red line indicates the observed number of variant-gene pairs

(41) shared with the 127 eQTL identified by Soskic et al. in a similar CD4+ T cell activation system.

(**B**) Prominent TF motifs predicted to be disrupted (blue) or stabilized (red) by promoter-connected

autoimmune SNPs. (**C**) 3D chromatin-based V2G genes are enriched for CRISPR-implicated

genes that regulate CD4+ T cell activation. Observed enrichment of genes regulating multiple

aspects of CD4+ T cell activation (IL-2, IL-2 receptor, CTLA-4, IFNg, TNFa or proliferation) from

CRISPR screens by Freimer, Schmidt, and Shifrut among sets of 3D chromatin-implicated genes

among individual diseases (green, FDR<0.05) or all diseases (purple, FDR<0.05). (**D**) Enrichment

for 3D chromatin-based autoimmune V2G genes among genes with germline knock-out mouse

immune (red) and other (black) phenotypes (adjP<0.05, IMPC database). (**E**) Autoimmune V2G-

implicated genes with at least one pharmacologic modulator (rDGIdb). (**F**) Comparison of the

number of manuscripts retrieved from PubMed related to autoimmune disease for each V2G gene

with pharmaceutical agents available (x-axis) with an immune-specific expression score

computed using the sum GTEX median expression values (v8) for whole blood or spleen divided

by other tissues (y-axis). Genes highlighted in red were selected for functional validation in **G**. (**G**)

Dose-dependent impact of the indicated pharmacologic agents targeting the V2G-implicated

genes *KISS1R, CHRNB, OXER1, GPR18, GRK6, PTK6, MAP3K11, GPR183, GART,* and *SIK1*

on proliferation of anti-CD3/28 activated murine (left) and human (right) CD4+ T cells *in vitro*

(N=4).

Supplemental Tables

Table S1: Expression and clustering of differentially expressed genes.

Table S2: Pathway enrichment of different RNA-seq genes

Table S3: Accessible chromatin regions

Table S4: Differential accessible open chromatin regions

Table S5: Differential contact frequency

Table S6: Differential TAD boundaries

Table S7: A/B compartment calls

Table S8: Stripe calls

Table S9: Summary of TF footprinting

Table S10: TF target gene pathway enrichment

Table S11: List of all GWAS studies included

Table S12: Variant to gene mapping across all timepoints

Table S13: Variant to gene mapping promoter OCRs

Table S14: Partitioned LD score regression output

Table S15: V2G genes implicated by orthogonal data

Table S16: Motifs predicted to disrupt transcription factor binding sites.

Table S17: V2G target gene drug repurposing results

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Figure 1

Figure 2

A — Chromatin accessibility dynamics (ATAC-seq)

B — AB compartment switching

C — TAD change 20%

D — Loop calls (HiC)

E — Differential loops (HiC)

F — Integrated accessibility, connectivity, and expression dynamics

Figure 3

Figure 4

Figure 5

Figure 6

Figure S1: **Library sequencing reproducibility and expression clustering.** (A) PCA of RNA-seq libraries. (B) PCA of ATAC-seq libraries. (C) Stratified correlation (SCC) of HiC libraries from two donors by stage of activation. (D) Volcano plot of RNA-seq data for CD4+ T cells unstimulated vs. 8 hr stimulation (top) and 8 hr vs. 24 hr stimulation (number of DEG indicated). (E) Elbow plot of the within group sum of squares used to determine optimal cluster number. (F) Genes per expression cluster. (G) Centroids +/- standard deviation for each cluster.

Figure S2: Characterization of CD4+ T cell epigenomic data. (A) Accessibility of OCR and (B) expression of genes located in A vs. B compartments (log2 fkpm). Differential accessibility (C) and expression (D) of cRE-gene pairs in regions exhibiting differential TAD structure. (E) Enrichment of promoter interacting region OCR for annotated regulatory elements in CD4+ T cells from the epigenome roadmap project (E038_15). (F) Overlap of cRE-promoter loops defined in this study to loops defined by Burren et al. in a prior promoter capture Hi-C study. (G) Distribution of OCR contacted per gene (top, median = 8 OCRs per gene). Distribution of genes contacted per OCR (bottom, median = 3). (H) Differential promoter-OCR connectivity by HiC as a function of differential OCR accessibility (central bar = median, boxplot edges = 25-75 quantiles, whiskers = 1.5x inter-quantile range).

Figure S3: Characterization of chromatin stripes during CD4+ T cell activation. (A) Stripes called per timepoint. (B) Proportion of SNPs annotated in A vs B compartments. Accessibility of OCR (C) and expression of genes (D) located in anchor (small more interactive region of stripe), stripe excluding the anchor (stripe), or outside stripes.

Figure S4: Large-scale epigenetic changes at dynamically expressed genes during CD4+ T cell activation. HiC contact frequency matrix (heatmap), chromatin accessibility (grey), and loop calls (red) for (A) GEM, (B) IRF4, (C) KLF2, and (D) DPEP2. The IRF4 matrix is truncated at by end of the chromosome annotation, and inset shows the expression (TPM) at each time point for each gene.

Figure S5: Enrichment of transcription family members and gene regulatory network construction. (A) -log10(P) enrichment of transcription factors annotated by family for each expression cluster. (B) Top five pathways enriched for a subset of TF-regulated gene expression.

Figure S6: TF occupancy and stability of distal IL2 cRE in CD4+ T cell subsets. Evolutionary conservation (blue), open chromatin (red), and autoimmune disease-associated SNPs at the IL2 locus in quiescent (A) and 8-hour activated (B) naïve CD4+ T cells. (C) Curated TF occupancy at the IL2 URR and distal cRE from the ReMap atlas of regulatory regions.

Figure S7: Orthogonal validation of 3D chromatin-based V2G genes. Expression (scaled TPM) of genes implicated by chromatin contacts in (A) prior colocalized CD4+ T cell single-cell eQTL27, (B) prior CRISPRi/a screens, and (C) genes with known immune phenotypes in the international mouse phenotyping consortium. Red = increased, blue = decreased.

Figure S8: Predicted impact of autoimmune disease-associated genetic variation at V2G-implicated loci. (A) Top 50 TF motifs impacted by autoimmune SNPs (excerpted from Table S15). (B) Genetic variation at the MS rs1077667 SNP is predicted to disrupt TP53, TP63, and POU2F2 (OCT2) binding sites. Dashed box indicates the SNP affected by allelic variation. HiC contact frequency matrix (heatmap), chromatin accessibility (grey), loop calls (blue-IL19/ITGA4, red-FAIM3) and predicted TF motif disruption for the rs3024505-IL19-FAIM3 T1D locus (C) and the rs1301071-ITGA4 celiac locus (D). SNP rs3024505 is predicted to disrupt a MZF1 motif and rs13010713 is predicted to disrupt a SOX4 binding motif.