

Characterising the genetic basis of immune response variation to identify causal mechanisms underlying disease susceptibility

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7	identify causal mechanisms underlying disease susceptibility
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39 Abstract (250 words)

Over the last ten years, genome-wide association studies (GWAS) have identified 40 41 hundreds of susceptibility loci for autoimmune diseases. However, despite increasing 42 power for the detection of both common and rare coding variants affecting disease 43 susceptibility, a large fraction of disease heritability has remained unexplained. In addition, a majority of the identified loci are located in non-coding regions, and 44 45 translation of disease-associated loci into new biological insights on the aetiology of 46 immune disorders has been lagging. This highlights the need for a better understanding of non-coding variation and new strategies to identify causal genes at 47 disease loci. In this review, I will first detail the molecular basis of gene expression 48 and review the various mechanisms that contribute to alter gene activity at the 49 50 transcriptional and post-transcriptional level. I will then review the findings from 10 51 years of functional genomics studies regarding the genetics on gene expression, in 52 particular in the context of infection. Finally, I will discuss the extent to which genetic variants that modulate gene expression at transcriptional and post-transcriptional 53 54 level contribute to disease susceptibility and present strategies to leverage these information for the identification of causal mechanisms at disease loci in the era of 55 56 whole genome sequencing.

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59 Introduction

The host immune response to stress exhibits considerable variation, both at the 60 individual and population levels¹. While many non heritable factors contribute to this 61 variability, including age, gender or past exposures to pathogens²⁻⁵ (see¹ for a review 62 63 on these aspects). There is also widespread evidence that genetics plays a significant role in determining the efficacy of the human immune response, in 64 particular in the context of innate immunity⁶⁻¹². Genome-wide association studies 65 (GWAS) have been a considerable asset in defining the genomic regions involved in 66 immune disease susceptibility¹³. However, identifying the causal mechanisms 67 68 through which GWAS variants contribute to disease susceptibility has proven to be extremely challenging. Indeed, it was soon realized that most GWAS pointed toward 69 gene deserts or non-coding regions^{14,15}, highlighting the strong need for 70 characterization of the molecular mechanisms through which such non-coding 71 regions may alter immune disease susceptibility¹⁶. Furthermore, while large GWAS 72 73 meta-analyses have granted increasing power to capture the effect of common variants on disease susceptibility, a large fraction of disease heritability has 74 remained unaccounted for¹⁷. There is now increasing evidence to suggest that rare 75 variants, non-coding in particular, may contribute to explain this missing heritability 76 ¹⁸⁻²⁰. Therefore, there is a growing need to understand how non-coding variants, 77

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78 whether rare or common, contribute to the variability of immune phenotypes in 79 humans. In this review, I will first present the various mechanisms though which noncoding elements may contribute to regulate gene expression, either at the 80 81 transcriptional level, or post-transcriptionally through RNA splicing and degradation. 82 Then, I will review current knowledge of how common genetic variants drive immune gene expression at the transcriptional and post-transcriptional level. Finally, I will 83 discuss strategies to decipher the impact of rare regulatory variants on immune 84 response and characterize the causal mechanisms that determine immune disease 85 86 susceptibility.

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88 The molecular bases of gene expression

89 In multi-cellular organisms, tight regulation of gene expression programs is essential. 90 First, during development, cells must coordinate expression of various transcription 91 factors to divide and differentiate into future organs. Then, in adult life, regulatory 92 sequence need to allow for cell-type specific gene expression profiles, that are both 93 (i) robust to genetic variations and (ii) able to react appropriately to external stimuli. In human, such combination of resilience and adaptability is achieved through a 94 95 network of regulatory features, the complexity of which largely exceeds that of the 96 protein coding genome. Indeed, while coding sequence represent only 1.5% of the

human genome, there is evidence that at least 20% of the genome is covered by
regulatory features, and 10% is actively bound by known transcription factors²¹.

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100 **Promoters and enhancers shape transcriptional activity across tissues**

101 The regulatory features that control transcription are characterized by epigenetic histone modifications (see **Table 1** and ref.²²) and can be decomposed in two main 102 103 categories (Figure 1a). At the transcription start site, promoters recruit RNA 104 polymerase, along with a variety of other transcription factors, to initiate gene transcription^{15,23,24}. While 96% of promoters are active in more than one tissue or cell 105 106 type, only ~20% are ubiquitously expressed indicative of strong tissue-specificity of gene regulation²³. Tissue-specificity is further increased by distal enhancer regions 107 - located up to 1Mb away from the promoters they regulate - which, when 108 109 activated by tissue-specific transcription factors, are brought in contact with their 110 associated promoter by looping of the DNA molecule (Figure 1b,c) to modulate their activity^{15,24,25}. Activation of both promoters and enhancers is associated to an 111 opening of the chromatin and acetylation of H3K27 histone residues (Figure 1d,e), 112 together with transcription of non-coding RNAs^{22,25,26}. This transcription occurs either 113 114 in the opposite direction of transcriptional elongation at promoters (upstream antisense RNAs), or bi-directionally for enhancers (enhancer RNAs). Although such 115

116 RNAs are rapidly degraded by exosomes, they allow precise quantification of 117 enhancer/promoter activity by sequencing techniques that target the 5' end of 118 transcripts such as CAGE-seq or GRO-Cap^{23,25,27}.

Over the last 10 years, large Consortia — such as Fantom5^{23,25}, ENCODE²⁶, 119 BluePrint²⁸⁻³¹ or Roadmap Epigenomic²² — have combined these techniques with 120 121 Chromatin immuno-precipitation (ChipSeq) and chromatin accessibility Assays 122 (DNAse-Seq, FAIRE-Seq, or ATAC-Seq) to precisely map promoters and enhancers along the genome and characterize of their activity across tissues. In doing so, 123 124 theses studies have provided valuable insights on the regulatory architecture of the 125 response to immune stimuli. Notably, immune enhancers were shown to have a distinct sequence composition, DNA structure and activity patterns³², with their 126 127 activation preceding that of their proximal promoters during immune response, revealing their crucial role in the early transcriptional response to immune stimuli³³. 128

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130 Three-dimensional chromatin conformation orchestrates transcription

Because enhancers are located far from the genes they regulate, understanding how they are brought into contact with their target gene is of primary importance to decipher the complex networks of that underlies transcriptional regulation in humans. Chromosome Conformation Capture techniques (Hi-C, and

135 Promoter-capture Hi-C, Chia-PET) have recently enabled the detection of DNA-DNA interactions along the genome^{30,31,34,35}, allowing the assignment of enhancers to their 136 137 target genes. In practice, a single gene is often regulated by multiple enhancers, and one enhancer can regulate multiple genes^{15,24}. Notably, ~70% of these interactions 138 139 are restricted to specific regions, known as Topologically associating domains or TADs, which can spread across hundreds of kilobases^{24,31}. The boundaries of these 140 TADs are genetically encoded — with evidence of TADs being modified by targeted 141 deletions and genetic variants occurring at the boundary^{35,36} — and are enriched in 142 143 are binding sites of the insulating factor CTCF. Note, however, that CTCF binding sites have also been observed within TADs³⁵, indicating that CTCF binding is not 144 sufficient to induce a TAD boundary. Growing evidence suggests that TADs act to 145 facilitate efficient and insulated co-regulation of functionally related genes. In 146 147 particular, they were reported to segregate promoters of immune gene together to facilitate their epigenetic priming³⁷. 148

Within TADs, promoter/enhancer conformation exhibits a wide variability across tissues, and was proposed to underlie cell type-specificity of enhancer functions³¹. In particular, several studies have reported the existence of enhancers acting as hubs for chromatin-chromatin interactions, linking promoters to other enhancers^{30,38,39}. These hubs — sometimes referred as super-enhancers³⁸,

frequently interacting regions³⁰ or initiator enhancers³⁹ — are tissue-specific³⁰, preferentially found next to cell identity genes^{30,38} and enriched in tissue-specific eQTL³⁹. More importantly, super enhancers are strongly enriched in disease-related SNPs and largely contribute to auto-immunity^{30,38}. For instance, up to 22% of SLE GWAS loci fall into B-cell specific super enhancers, with disease-linked superenhancers being observed at key immune genes such as HLA-DRB1, HLA-DQA1, the interferon response factor IRF5 or the NF- κ B inhibitor TNFAIP3³⁸.

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162 **Post-transcriptional regulation through alternative splicing**

163 Beyond transcription, the control of gene expression is also ensured at the 164 post-transcriptional level through alternative splicing (AS) and miRNA-mediated 165 degradation. AS can change the function of the protein isoform that is being 166 expressed, through addition/removal of exons encoding functional domains. The most iconic example of such a mechanism is the splicing transition of CD45 antigen 167 168 during training of adaptive immunity, where T-cells switch from the CD45RO epitope 169 that characterizes naïve T-cells to the CD45RA epitope associated with memory Tcells⁴⁰. AS can also repress gene expression through the introduction of premature 170 stop codons into transcribed sequences, leading to non-sense mediated decay^{41,42}. 171 172 Although our understanding of the splicing code remains incomplete, there is a wide agreement that it involves the recognition by the spliceosome of donor/acceptor 173

174 sequences located at the intron boundaries, together with a branchpoint sequence — typically located ~30 nucleotide upstream of the acceptor splice site^{41,42}. This 175 leads to the formation of a lariat and the removal of the intron. AS is induced by 176 177 competition between splice sites and is regulated through a wide array of RNA binding proteins able to recognize both exonic and intronic regulatory sequences⁴²⁻ 178 179 ⁴⁵. These sequences can act as to either repress or promote, the recruitment of the 180 spliceosome around a specific splice site or exon. In addition, alternative splicing can also be regulated co-transcriptionally, with exon inclusion being associated to a 181 lower transcriptional elongation rate around the alternatively spliced exon⁴¹. 182

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184 Impact of miRNA-mediated degradation on immune response

Another layer of post-transcriptional regulation occurs through the binding of 185 186 miRNAs to 3'UTRs, and the targeting of bound mRNAs to the RNA induced silencing complex (RiSC)^{46,47}. The RISC then functions to repress gene expression through 187 188 degradation of transcripts and inhibition of translation. For example, upon TLR4 189 stimulation, the NF-kB-activated miRNAs mir-146a and miR-155 are strongly up-190 regulated and bind to 3'UTRs of the TLR4 signal transducers, TRAF6 and IRAK4 and the TLR4 inhibitors SHIP1 and SOCS1⁴⁸, respectively. These mRNAs are then 191 targeted to the RISC for degradation, thereby contributing to the balance of 192

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193 inflammatory responses to TLR4 stimulation. Several mechanisms can further 194 modulate the impact of miRNAs on gene expression. For instance, usage of alternative UTRs and poly-adenylation sites can change the set of miRNA binding 195 sites available for regulation of gene expression⁴⁹. Such changes have been shown 196 to be widespread upon stimulation⁴⁹ and to play an important role in allowing key 197 regulators of immune response, such as IRF5 or Map Kinases MAPKAP1 and 198 MAP2K4, to escape repression by immune miRNAs⁴⁹. Formation of miRNA isoforms 199 - known as isomiRs - could also contribute to immune response variability. 200 201 Indeed, it was shown that post-transcriptional modifications of miRNAs through 202 editing of the miRNA seed sequence or shifts in 5'/3' boundaries of the mature 203 miRNA, can alter their target sites or stability and lead to a decrease in their ability to for regulate mRNAs^{46,50}. Furthermore, extensive changes in isomiRs have been 204 observed upon stimulation, including for key immune miRNAs⁵¹. For instance, upon 205 206 stimulation by interferon, mir-222 expresses shorter isoforms, which are associated to lower apoptosis^{52,53}, highlighting how changes of miRNA isoform can contribute to 207 208 regulate the response to immune stimuli.

210 The genetic bases of gene expression

One major challenge of functional genomics is the understanding of the regulatory code that dictates gene expression from the genetic information encoded by DNA sequences. One approach to learn this regulatory code is through the use of naturally-occurring genetic variation. Studies of expression quantitative trait loci (eQTL) aim to identify genetic variants that are associated to gene expression levels in human populations.

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218 Genetic control of transcriptional activity is highly stimulation-specific

219 eQTL studies have first focused of steady-state expression measurements on lymphoblastoid cell lines or whole blood, from a wide range of populations⁵⁴⁻⁵⁸. 220 These studies are revealed that the majority of eQTLs are located in cis, i.e. less 221 than 1Mb away of the gene they control, and that population-specific eQTLs are 222 driven by changes in allelic frequency rather than gene × gene or gene × 223 environment interactions⁵⁹. While a few *trans*-associations — involving genes 224 225 located on different chromosomes --- were detected, these associations were either weak or driven by cross mapping errors⁶⁰ and changes in cellular composition⁶¹. The 226 strong potential of eQTL for biomedical applications⁶² has rapidly lead to extend this 227 framework to multiple tissues⁶³ or purified immune cell types^{29,64}, revealing a strong 228 tissue specificity of eQTLs. Furthermore, exposing human cells to immune and 229

230 infectious challenges has allowed the identification of response eQTLs that are 231 associated with changes in gene expression specifically upon immune stimulation (Figure 1f,g)^{6,9,12,65,66}. Interestingly, response-eQTLs were found to be highly 232 variable across stimuli and time points^{8,9,12}. For instance, the rs9266257 variant was 233 234 found to control expression of HLA-C in macrophages specifically upon infection by Salmonella, but not Listeria⁶⁵. Interestingly, this phenomenon appeared even more 235 striking among trans-eQTLs which where often revealed by immune stimulation⁸. An 236 237 outstanding example of this is the TLR1 locus, where the European-specific 238 missense variant rs5743618 is associated with a decreased inflammatory response to stimulation of the TLR1/2 complex⁹. Interestingly, the European-specific allele of 239 this variant is protective against leprosis⁶⁷ and overlaps one of the strongest 240 signature of natural selection in the human genome⁹, highlighting how selective 241 pressures induced by pathogens can lead to strong inter-individual and inter-242 243 population differences in immune phenotypes.

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245 **The subtle effect of enhancer variants of gene expression**

Studies of the mechanistic bases of eQTLs^{9,57} have shown that promoter variants are largely overrepresented among eQTLs. However, enhancer variant are increasing likely to be found when focusing on secondary, weaker eQTLs⁶³. The

increasing power to detect small effect size and highly localized effects offered by 249 eQTL meta-analyses⁶¹ and analyses of eQTLs at single cell resolution⁶⁸ will likely 250 improve our understanding of the contribution of enhancer variants to gene 251 252 expression. Another approach to detect subtle effects of enhancers variants on gene 253 expression consists in assaying directly the effect of genetic variants on regulatory activity, based on chromatin accessibility^{66,69}, histone modifications^{29,69}, or short-live 254 transcriptional products⁷⁰. In doing so, Li *et al.* estimated that QTLs for regulatory 255 elements could account for ~60% of eQTLs, but only <25% of enhancers QTLs were 256 associated to an effect on transcription nearest gene⁶⁹, suggesting that only a small 257 258 fraction of variants that alter regulatory activity lead to a measurable effect on gene expression. However, variants that alter chromatin accessibility with no visible effect 259 on gene expression at basal state can contribute to prime enhancers⁶⁶. Upon 260 stimulation, this priming favours the binding of stimulus-specific transcription factors, 261 such as NF- κ B or Stat2, leading to a stronger immune response^{37,66}, Together, these 262 263 observations highlight the potential of eQTL meta-analyses and direct assays of 264 regulatory activity to understand inter-individual variability in immune response.

266	Genetic regulation of post-transcriptional variability in the immune response
267	Perhaps unsurprisingly given their strong potential to alter protein function,
268	splicing quantitative trait loci (sQTLs, figure 2a) have turned out to be consistently
269	less frequent than eQTLs across the human genome. Indeed, eQTLs appear to be
270	from 1.5 to 6 time more frequent than sQTLs, across studies ^{56,57,58,65,71,72} (Table 2).
271	In addition, sQTLs displayed a stronger overlap between conditions of stimulation
272	than eQTLs ^{65,71} , suggesting a limited impact of stimulation on the genetic regulation
273	of splicing. Nevertheless, disease-causing sQTL have been observed at many key
274	immune genes including OAS1, IRF7, IL7R, IFI44L, TYK2 and ERAP2 ^{65,71,73-75} ,
275	highlighting the importance of considering splicing variation when searching for the
276	causal mechanisms underlying GWAS loci. Interestingly, several of these loci,
277	including OAS1 or ERAP2 present haplotypic signatures of positive and balancing
278	selection, suggesting that these sQTL have conferred a selective advantage to
279	human populations in the past, likely through increased resistance to pathogens. ^{71,73} .
280	The regulation of miRNA expression has also been extensively studied, both at basal
281	state ^{76,77} and in response to infection ⁷⁸ . Similar to splicing, miRNA QTLs studies
282	(figure 2b) have generally suggested a limited genetic control of miRNAs, consistent
283	with expectation of strong selective constraints on miRNA expression due to their

284	widespread impact on gene expression ^{76,78} . miRNA QTLs appear to be strongly
285	enriched in variants located in their promoter and eQTLs of their host gene ⁷⁹ .
286	However, there is also strong evidence that enhancers and loci that are bound by
287	transcription factor (TF) contribute to miRNA expression ⁷⁷ . Recently, a study has
288	used models of SNP-miRNA interactions to quantify the impact of SNPs on the
289	regulation by miRNAs (reg-eQTL, figure 2c). This has lead to the identification of
290	~40 SNP that disrupt miRNA binding sites ⁸⁰ . The proposed approach, however,
291	suffers from the lack of power usually associated with interaction testing, and may
292	largely underestimate the true number of such reg-eQTL. Larger studies combining
293	expression, genetic and miRNA data are now needed to fully characterize the impact
294	of genetic variants on miRNA-mediated degradation in the immune response.

296 The contribution of regulatory variants to disease susceptibility

In support of the importance or eQTLs in disease susceptibility, they have been repeatedly reported to be enriched in disease loci^{8,9,12,57,63}. For instance, the association of the rs4077515 variant with Inflammatory bowel disease is mediated by activation of a distal enhancer of *CARD9* leading to an increase of its transcription, supporting the causal role of CARD9 in Inflammatory bowel disease²⁹. Similarly, there is increasing support to the notion that sQTL or mirRNA QTLs can also

contribute to common disease risk^{69,71,81}. For instance, the Multiple sclerosis 303 304 associated variant rs6897932, located within an exon 6 of IL7R, has been shown to promote exon skipping. As a result, a soluble form of IL7R is being produced that is 305 associated with exacerbated auto-immune phenotypes in mice⁷⁵. However, despite 306 307 evidence that 90% of auto-immune loci act through regulatory variants, 60% of which are located at enhancers⁸², it was suggested that only a limited fraction of the QTLs 308 detected at GWAS loci play a causal role in disease susceptibility^{63,83}. This 309 observation, which may reflect the robustness of disease gene expression induced 310 by the high redundancy of their enhancers⁸⁴, highlights the importance of taking 311 312 linkage disequilibrium into account when assessing the co-localization between GWAS loci and eQTLs, or sQTLs⁸⁵. 313

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315 Deciphering the regulatory code to predict the effect of rare variants

Recently, the development of massively parallel reporter assays (MPRA) has enabled the direct assessment of cis-regulatory activity associated to specific DNA fragments, either synthetic⁸⁶, or naturally occurring^{87,88}. The general principle of MPRA techniques (**figure 3**) consists in transfecting libraries of barcoded plasmids into live cells and counting the occurrence of each barcode in the transfected cells, as a measure of the activity of the associated regulatory sequence (after

322	normalization by the barcode frequency in the initial library). By measuring the
323	activity of both alleles at heterozygous loci, these approaches further allow
324	quantifying the impact of genetic variants, or haplotypes, from a single individual.
325	Thus, they constitute a privileged tool for assessing the impact of rare variants on
326	regulatory regions, or identifying causal variants among sets of linked SNPs
327	identified through eQTL analyses ^{88,89} . For instance, dissection of regulatory
328	mechanisms at a 87 nucleotide-long IFNB1 enhancer indicated that 83 substitutions,
329	out the 261 possible, resulted in altered activity in virus-infected cells ⁸⁸ .
330	Massively parallel assays have also been used in the context of both splicing ^{90,91}
331	and miRNA-mediated regulation ^{92,93} , revealing, for instance, that up to 16% of splice
332	disrupting variants are located in deep intronic regions ⁹⁰ . With the development of
333	deep learning frameworks for sequence-based predictions ^{94,95} , data generated by
334	these assays, will now fuel the construction of predictive models. These models will,
335	in turn, allow quantifying the regulatory impact of novel genetic variants on
336	transcriptional activity ⁸⁸ , alternative splicing ⁹⁶ , or miRNA-mediated regulation ⁹³ .
337	
338	Concluding remarks: a strategy for the future.
339	Elucidating the mechanisms by which non-coding variants contribute to the inter-

340 individual variability of immune response is now an essential step in order to

translate the findings of epidemiological genetic studies into the clinics¹³. The 341 characterization the human epigenome across a wide variety of tissues and 342 conditions has allowed establishing a first map of the regulatory landscape of the 343 human genome. Further efforts are now needed to fully define the cascade of 344 345 regulatory events that take place during the immune response, for a wide spectrum of stimuli and with a high temporal resolution. This will allow classifying regulatory 346 347 elements according to their activity in distinct cell types, and in response to specific stimuli. Then, using heritability partitioning techniques^{97,98} that decompose the 348 349 genetic variance of complex traits across several SNP categories, we will be able to 350 identify the cell types and stimuli that most strongly contribute to the development of immune disorders. Holistic studies that consider both transcriptional and post-351 transcriptional aspects of gene expression variation^{41,66,74}, and combine RNA seq 352 with sequencing of small RNAs or ATAC-seq, constitute a promising approach to 353 354 understand the aetiology of immune disorders. Such approaches, however, are only 355 the first step toward the identification of the causal mechanisms that underlie disease 356 susceptibility. Validation of the proposed mechanisms, through colocalization analysis⁸⁵, mendelian randomization approaches⁹⁹ and randomized clinical trials¹⁰⁰, 357 358 are then required to formally establish causality. Finally, as whole genome sequencing is becoming increasingly common¹⁹, the ability to identify rare regulatory 359

360	variants at known	disease genes	will become a	crucial step	toward personalized
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- treatments of both rare and common immune disorders. In this context, the
- 362 increased knowledge of the regulatory code granted by functional genomics studies,
- 363 and MPRA in particular, will constitute a precious tool to predict and assess the
- 364 effect of rare variants on intermediate disease phenotypes.

Epigenetic mark	Associated function	Assay	
H3K4me1	Enhancers	Chip-Seq	
H3K4me3	Promoters	Chip-Seq	
	Active regulatory regions	Chip Sec	
TISK27AC	(promoter/enhancer)	Chip-Seq	
	Active regulatory region	Chin Soa	
IJNAC	(promoter/enhancer)	Chip-Seq	
H2K26mo2	transcribed regions	Chin Soa	
TISKS0IIIe5	/exon definition	Chip-Seq	
H3K0me3	repressed region	Chin Soa	
TISKelles	(heterochromatin)	Chip-Seq	
H3K27me3	repressed region	Chin-Sea	
TISK27THE5	(polycomb)	Chip-Seq	
Cytosine	repressed regulatory		
methylation	regions (promoter/enhancer)	DisuilleSeq	
Open Chromatin	Active regulatory region	DNAse-Seq/	
	(promoter/enhancer)	ATAC-Seq	

Table 1. *Epigenetic marks associated with gene regulation*

368Table 2. Compared number of eQTL and sQTL detected across studies

Study	Sample used	Number of eQTL detected	Number of sQTL detected	Metric used	
Pickrell, 2010 ⁵⁶	lymphoblastoid cell lines (n=69)	929	187	Exon	
Lappalainen, 2013 ⁵⁷	lymphoblastoid cell lines (n= 462)	3,773	639	Transcript	
Battle, 2014 ⁵⁸	Whole blood (n=922)	10,914	2,851	Transcript	
Nedelec, 2016 ⁶⁵	macrophages (n=175 x 3 conditions)	1,647	1,120	Transcript	
	Monocytes,	6513,	3044,	Transcript	
Chen, 2016 ²⁹	neutrophils,	5845,	2034,	Evon	
	CD4+ T-cells (n=197)	5799	3347	EXUIT	
Ye, 2018 ⁷¹	Dendritic cells (3 conditions, n= 99+227+250)	6,694	2,763	Transcript	





a. Genomic dissection of a genic region. Grey arrow represents the transcription

373 start site. Purple, green and orange lines represent possible chromatin-chromatin

374 interactions between enhancers, or between enhancers and the promoter.

375 Green/red circle represents a mutation of the orange enhancer. The same color

376	code is used throughout the figure. b-c . 3-dimensional representation of
377	chromatin interactions leading to gene expression. At basal state (b), gene
378	expression is mediated by the green enhancer, which comes in contact with the
379	promoter (lightblue) and recruits the purple enhancer. Upon stimulation (${f c}$), the
380	green enhancers is sequestrated far from the promoter and replaced by the
381	orange enhancer, allowing the mutation to alter gene expression. d-e. Activity of
382	regulatory elements in the region, at basal state (d) and upon stimulation (e).
383	Peaks indicate H3K27 acetylation with measures activity at promoters and
384	enhancers. f-g . Boxplots of gene expression for each genotype, at basal state (f)
385	and upon stimulation (g). Alleles at the locus are colour coded (red: low
386	expression, green: high expression allele). The impact of the genetic variant
387	located in the orange enhancer is visible only in the stimulated condition, where
388	the enhancer is active.
389	





a. sQTL alter gene function by changing their splicing, leading to a different protein
isoform. b. miRNA QTL that modify the abundance of miRNAs can act in *trans* in to
alter gene expression of genes located elsewhere on the genome through miRNAmediated degradation. c. SNPs that disturb (or create) miRNA binding sites in the
3'UTR of a gene can also change their level of expression, by acting in *cis* on
miRNA-mediated degradation. Such SNPs are referred as reg-eQTLs.



401 Figure 3: Principle of massively parallel reporter assays (MPRA).

402 MPRA consists in forming libraries of putative regulatory sequences, where each 403 sequence is associated to a specific, random barcode (1). The barcoded sequence 404 is then introduced in a reporter plasmid, where it is ligated to the 3' of a green 405 fluorescent protein (GFP) associated with a basic promoter sequence (2). The 406 plasmid library is then transfected into a cell line representative of the tissue of 407 interest (3). RNA from GFP positive cell are harvested and mRNAs of the reporter 408 gene are captured and sequenced (4). The regulatory activity of each sequence is 409 then measured by comparing the counts of its associated barcode in the transfected cell library with that of the initial sequence library (5). 410

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- 416

417 Biosketch.

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419 Dr Maxime Rotival obtained his PhD in statistical genetics in 2011 from University of 420 Paris-Sud/XI. His PhD work regarded the genetic determinants of monocyte gene 421 expression in humans and their contribution to metabolic and cardiovascular 422 disorders. He did his first postdoc at Imperial College London, where he studied the 423 genetics of macrophage dysfunction in a rat model of chronic kidney inflammatory 424 disease, before joining the Human Evolutionary Genetics laboratory of Institut 425 Pasteur (CNRS UMR2000) in 2014. There he studied how genetic variants that alter 426 response to immune stimuli have contributed to the adaptation of modern human 427 population to pathogens present in their environment. He now has a researcher 428 position at institut Pasteur and is interested in the contribution of genetic diversity to 429 the inter-individual variability in innate immune response and how selective 430 pressures induced by pathogens have shaped this diversity. His work was awarded 431 with the Julia Bodmer Award for Young Scientists from the European Federation for 432 Immunogenetics in 2018.

433

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