

Immune transcriptomic differences in paediatric patients with SARS-CoV-2 compared to other lower respiratory tract infections

Negusse Tadesse Kitaba¹, Lesley Workman², Cheryl Cohen^{3,4}, Diana Baralle^{1,5,6}, Ellen Kong⁷, Maresa Botha², Marina Johnson^{8,9}, David Goldblatt^{8,9}, Mark P Nicol¹⁰, John W Holloway^{1,6#} and Heather J Zar^{2#}

#These authors contributed equally: Heather J Zar & John W. Holloway.
Corresponding author: Heather J Zar heather.zar@uct.ac.za

¹Human Development and Health, Faculty of Medicine, University of Southampton, Southampton, UK

²Department of Paediatrics and Child Health, Red Cross War Memorial Children's Hospital and SA-MRC Unit on Child & Adolescent Health, University of Cape Town, Cape Town, South Africa

³Center for Respiratory disease and Meningitis, National Institute for Communicable Diseases, a division of the National Health Laboratory Service, 1 Modderfontein Road Sandringham, South Africa

⁴School of Public Health, University of the Witwatersrand, Johannesburg, South Africa

⁵National Health, Service (NHS) Foundation Trust Southampton, UK

⁶NIHR Southampton Biomedical Research Centre, University Hospitals Southampton, Southampton, UK

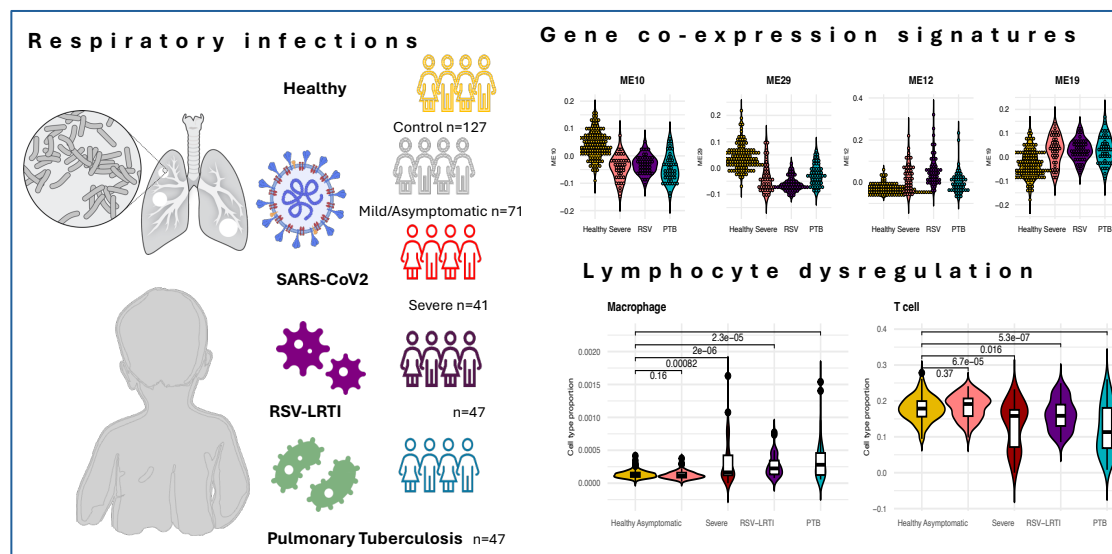
⁷National Heart and Lung Institute, Imperial College London, London, UK

⁸Great Ormond Street Institute of Child Health University College London, UK

⁹National Heart and Lung Institute, Imperial College London, London, UK

¹⁰The University of Western Australia: Perth, Australia

Graphical abstract



Abstract

The clinical severity of SARS-CoV-2 infection in children varies, with asymptomatic or mild illness predominating and a minority developing severe disease. Understanding the immunological responses that underlie severity of disease may guide future development of preventive or therapeutic interventions. This study compared whole blood transcriptomes of healthy children (N=127), children with mild/asymptomatic SARS-CoV-2 infection (N=71) and children hospitalised with severe SARS-CoV-2 (N=41), lower respiratory tract illness (LRTI) or LRTI due to Respiratory Syncytial Virus (RSV-LRTI) (N=47) or Pulmonary Tuberculosis (PTB) (N=47). We identified >5000 differentially expressed genes including: *OLFM4*, *IFI27*, *CBX7*, *IGF2BP3*, *OTOF* for severe SARS-CoV-2; *IFI27*, *OTOF*, *SIGLEC1*, *IFI44L* and *USP18* for RSV-LRTI, and *MMP8*, *LTF*, *IGF2BP3*, *GPR84*, *CD177*, *CIQC* and *DEFA4* for PTB, at false discovery rate (FDR) <0.05. Pathway analysis identified enrichment for neutrophil degranulation, interferon gamma signalling, overexpression of ribosomal proteins and depletion of immune response in severe SARS-CoV-2 compared to healthy (SARS-CoV-2 uninfected) children. Weighted Gene Co-expression Network Analysis (*WGCNA*) identified 10 correlated gene modules shared between LRTI showing similar underlying response mechanisms. Cellular decomposition analysis identified the depletion of 22 cell types in severe SARS-CoV-2, 16 for RSV-LRTI and 21 for PTB compared to healthy SARS-CoV-2 uninfected control children. We identified 82 genes important for discriminating asymptomatic/mild from severe SARS-CoV-2 including *CBX7*, *TRAF1*, *ZNF324* and *CASS4*; 93 healthy from severe SARS-CoV-2 including *RORC*, *CBX7*, *NR3C2*, *MID2* and *ADAMTS2*; 110 genes for RSV-LRTI and 95 for PTB children which can be used for future therapeutic targets.

Keywords: Respiratory infection, Covid-19, PTB, RSV-LRTI, WGCNA, Child

24 Introduction

25 Lower respiratory tract illness (LRTI) is a major cause of hospitalisation and mortality globally in
 26 children, with the burden heavily skewed to low- and medium-income countries (LMICs). RSV
 27 predominates as a cause of severe LRTI and hospitalisation. Pulmonary tuberculosis (PTB) has
 28 also increasingly been recognised as an important cause of acute LRTI in children in countries in
 29 which TB is endemic¹. During the SARS-COV-2 pandemic, SARS-CoV-2 emerged as a cause of
 30 LRTI in children.

31 The clinical manifestation of COVID-19 in children varies widely from mild or asymptomatic
 32 illness to severe LRTI², although severe disease is rare. Immunologically, the hallmarks of
 33 COVID-19 include dysregulation of type I IFN activity, hyperinflammation, lymphopenia,
 34 heterogeneous adaptive immunity, dysregulated myeloid response and lymphocyte impairment^{3,4}.
 35 COVID-19 severity is also associated with different levels of neutralizing antibodies^{5,6}. While the
 36 blood transcriptomic response to SARS-CoV-2 infection has been described in adults^{7,8,9}, few
 37 studies have investigated responses to SARS-CoV-2 in infants and children^{10,11} and little is known
 38 about differences in host gene expression between children asymptomatic with SARS-CoV-2
 39 infection and those hospitalized with severe COVID-19 or other LRTI such as Respiratory
 40 Syncytial Virus (RSV-LRTI) or pulmonary tuberculosis (PTB)^{12,13,14,15}.

41 A multi-omics approach has previously shown utility in characterising the complexity and severity
 42 of Covid-19¹⁶. Weighted Gene Co-expression Networks Analysis (WGCNA) is a widely
 43 implemented approach to identify co-regulated genes and potential hub-genes for druggable
 44 targets¹⁷. The aim of this study was to compare host RNA gene expression in healthy children
 45 compared to those with asymptomatic or mild SARS-CoV-2 infection, as well as to those

hospitalised with COVID-19, RSV-LRTI or PTB and to utilise WGCNA to identify underlying immune responses associated with disease.

Methods

This was a prospective study conducted during the SARS-COV-2 pandemic that investigated patterns of whole blood gene expression in HIV-negative children enrolled in a South African birth cohort study, the Drakenstein Child Health study (DCHS), and those hospitalised with SARS-COV-2 (severe COVID-19), RSV-LRTI or PTB.

Participants

Healthy controls or previous SARS-CoV-2 mild or asymptomatic infection: Participants were from the Drakenstein Child Health Study, a prospective population-based birth cohort study of children in a low- and middle-income, peri-urban community outside Cape Town, South Africa¹⁸. In the DCHS, during the SARS-CoV-2 pandemic, a convenience sample of a subset of children (N=201) was included in intensive surveillance for SARS-CoV-2 infection with blood sampling every 3 months from 15-May-2020 through 15-Sept-2022, with blood and nasopharyngeal swabs collected, irrespective of symptoms.

In addition, continuous surveillance for illness or hospitalisation was undertaken, and blood and nasal sampling repeated at any intercurrent illness. Serum samples were stored and batched for measurement of IgG to Spike antigen (CoV-2-S-IgG) by ELISA as previously described¹⁹. In the current study, samples from children during wave 1 were used; subjects seronegative for SARS-CoV-2 were defined as healthy controls, and those seropositive for SARS-CoV-2 were considered mild/asymptomatic infection as no child reported symptomatic illness or was hospitalised.

68 **Children with LRTI**

69 **COVID-19 or RSV-LRTI:** Children with acute LRTI hospitalised at Red Cross Childrens
 70 Hospital were identified through the National Syndromic Surveillance for pneumonia in South
 71 Africa programme (PSP) at Red Cross War Memorial Children's Hospital, in Cape Town, South
 72 Africa. Sequential children hospitalised with LRTI were enrolled and a nasal swab for PCR
 73 detection of SARS-CoV2, RSV and other pathogens was taken for testing at National Institute of
 74 Communicable Disease as previously described²⁰. Children who were positive for SARS-CoV-2
 75 and negative for other pathogens were considered to have severe COVID-19 (N=41); those
 76 positive for RSV were included as RSV-LRTI (N=51).

77 **PTB:** Children enrolled in a TB diagnostic study (N=47) at Red Cross Children's Hospital,
 78 microbiologically confirmed (by mycobacterial liquid culture or Xpert MTB/RIF) and negative
 79 for SARS-CoV-2 and RSV, were included in this study. Serum and PAXgene samples were
 80 collected at the time of illness (Severe COVID-19, RSV-LRTI, PTB) were used for this study²⁰.
 81 Whole blood PAXgene samples were stored at -80°C, randomized prior to shipment, with RNA
 82 extraction and sequencing undertaken at the Genomics Shared Resource (GSR), Roswell Park
 83 Comprehensive Cancer Centre, Buffalo NY, USA.

84 **Sequencing and processing RNAseq data**

85 Raw reads were processed with the bcbio-nextgen pipeline. Reads quality were assessed using
 86 FastQC²¹ and MultiQC²². Sequencing reads were aligned to the human transcriptome reference
 87 using STAR²³. Quantification of gene expression was carried out using Salmon²⁴ with default
 88 settings. Read counts were normalized using CPM (counts per million) from edgeR²⁵ with the
 89 TMM (Trimmed Mean of the M-values) method which accounts for both sequencing depth and

gene length²⁶. Sample outliers were detected using Robust Principal Component Analysis (rPCA) with PcaHubert and PcaGrid functions²⁷; samples detected by both methods were excluded from downstream analysis.

Identification of differentially expressed genes (DEGs)

Amongst 198 children in DCHS, 64% were seronegative (N=127) and regarded as healthy controls. Those were compared to hospitalised children with COVID-19 (N=41), RSV-LRT (N=47) or PTB (N=47). SARS-CoV-2 seropositive during wave 1 (N=71), who did not report any respiratory symptoms or hospitalization over this period, were regarded as having had mild or asymptomatic infection.

The R-package limma²⁸ was used to identify differentially-expressed genes adjusting for children's sex and age. Multiple testing correction was performed using the Benjamini-Hochberg (BH) procedure for False Discovery Rate (FDR) < 0.05. The biological function of gene lists were identified via gene set and pathway enrichment analyses using topGene²⁹.

Weighted Gene Co-expression Network Analysis (*WGCNA*)

Signed weighted gene co-expression network analyses were conducted using WGCNA³⁰. The gene module/clusters represent genes with highly correlated expression patterns, where the first principal component of the gene expression profile (Eigengene) is used to summarise the overall expression of each module. The module eigengenes identified by WGCNA were correlated with Severe COVID-19, PTB and RSV-LRTI. The module associations were visualised as a correlation barplot using the lares R package³¹. Protein-Protein Interaction (PPI) network were identified with GeneMANIA³² and network properties for hub genes were analysed and visualized using Cytoscape³³. Significantly associated modules were further characterized for functional

112 enrichment using topGene²⁹. Non-redundant biological process terms were generated and
113 visualized using rrvgo package³⁴.

114 Cell type proportion estimation

115 Cell type proportion differences between groups were estimated and assessed using xCell 2.0³⁵
116 using the Immune Compendium³⁶ and immunoprofiling³⁷ reference datasets. The t-test was used
117 to determine the difference between groups (asymptomatic vs hospitalized SARS-CoV-2 , control
118 vs RSV-LRTI and control vs PTB).

119 Severity predictors

120 Gene biomarkers to predict SARS-CoV-2 severity, RSV-LRTI or PTB were selected using the
121 Boruta³⁸ R package³⁹ with default settings.

122 Gene and target drug look-up

123 In order to identify the druggability of differentially expressed genes, the look-up target score
124 generated by DrugnomeAI⁴⁰ was utilised (accessed on 19 March 2025). All statistical analyses
125 were conducted in R version 4.5.1.

126

Results

Participant characteristics.

This analysis includes 333 children: 71 with previous mild/asymptomatic SARS-CoV-2, 127 seronegative, healthy, and 135 children hospitalised with LRTI (41 with SARS-COV-2, 47 with RSV-LRTI and 47 with PTB or pulmonary TB). The characteristics of each group are shown in Table 1. As there was a significant age difference between DCHS children and those with LRTI, age was included as a covariate in regression analyses.

Table 1 Comparison of participants' characteristics for healthy controls and children with respiratory tract infections

Variable	Healthy SARS-CoV-2 seronegative	Mild/asymptomatic SARS-CoV-2 infection		Severe COVID-19		RSV-LRTI		PTB	
	N = 127	N = 71	p-value ²	N = 41	p-value ²	N = 47	p-value ²	N = 47	p-value ²
Gender									
Male	65	28	0.11	24	0.4	28	0.3	27	0.5
N (%)	(51%)	(39%)		(59%)		(60%)		(57%)	
Age									
(months)	81	83	0.4	11	<0.001	7	<0.001	8	<0.001
Median	(71, 87)	(72, 90)		(3, 45)		(2, 22)		(4, 40)	
(Q1, Q3)									
Healthy: DCHS children seronegative for SARS-CoV-2 in wave 1 of the Covid-19 pandemic; Mild/asymptomatic: DCHS children seropositive for SARS-CoV-2 in wave 1; Severe COVID-19: Children admitted with COVID-19 lower respiratory tract infection (LRTI) and not co-infected; RSV-LRTI: children admitted with Respiratory Syncytial Virus LRTI; PTB: children with pulmonary tuberculosis infection.									

Differential gene expression analysis

To identify differentially expressed genes and enriched GO terms in children with LRTI, seronegative DCHS participants from wave 1 (healthy controls) were compared to each LRTI

group separately (COVID-19, RSV-LRTI, PTB). The summary statistics and gene lists for TWAS at FDR <0.05 are provided in Supplementary Table S1. The biological gene ontology enrichment is also provided in Supplementary Table S2.

COVID-19 disease

The transcriptional response in healthy controls was compared to hospitalised children with COVID-19. There were 118 up-regulated and 160 down-regulated differentially expressed genes (DEGs) between healthy control and severe SARS-CoV-2 cases (FDR < 0.05 and log2 fold change >1), as shown in Figure 1A. Top DEGs included: *IFI27*, *MMP8*, *OLFM4*, *CEACAM8*, *LTF*, *IGF2BP3*, *DEFA4*, *ADAMTS2* and *CBX7*. Pathways identified as enriched include regulation of immune system and lymphocyte activation (Figure 2A).

RSV-LRTI

DGE analysis identified 210 upregulated and 195 downregulated genes at FDR < 0.05 and log2 fold change >1 and differentially expressed between healthy controls and children hospitalized with RSV-LRTI; top DEGs included *IFI27*, *OTOF*, *SIGLEC1*, *IFI44L*, *USP18*, *TCN2*, *CD177*, *HERC6*, *CIQC* and *EPHB2*. For all summary statistics see RSV-LRTI in Table S1 and the volcano plot shown in Figure 1B. Pathways significantly enriched included regulation of immune system translation, interferon mediated signalling, viral life cycle and viral processing (Figure 2B).

Pulmonary Tuberculosis

Children with PTB had identified 203 upregulated and 1843 downregulated genes differentially expressed genes (FDR < 0.05 and log2 fold change >1) compared to healthy controls. Top genes identified include *MMP8*, *LTF*, *IGF2BP3*, *GPR84*, *CD177*, *CIQC*, *DEFA4* and *OLFM4* (see

Figure 1 and Supplementary table S1). The pathways identified as enriched include defence response to bacteria, and innate immune response (see PTB in Figure 2C).

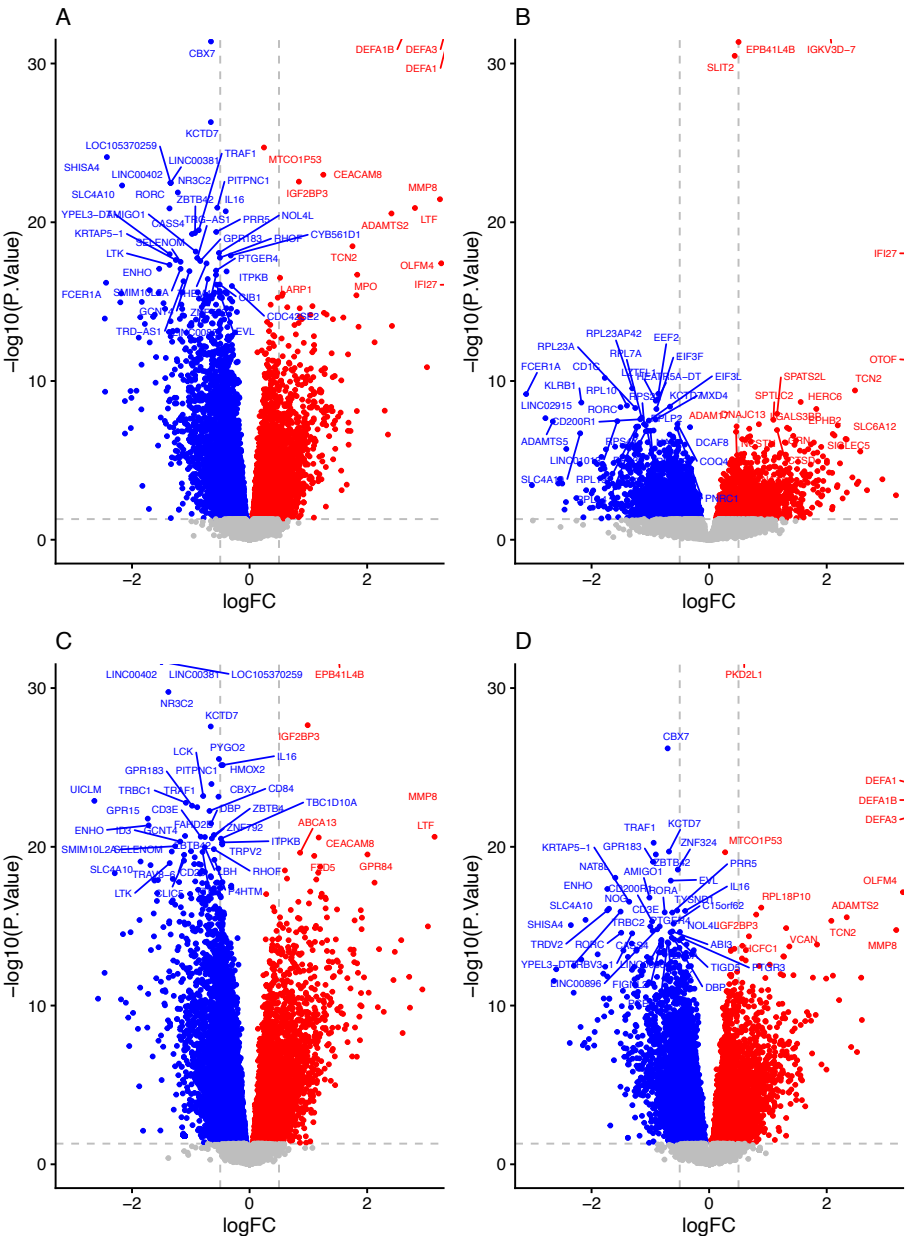
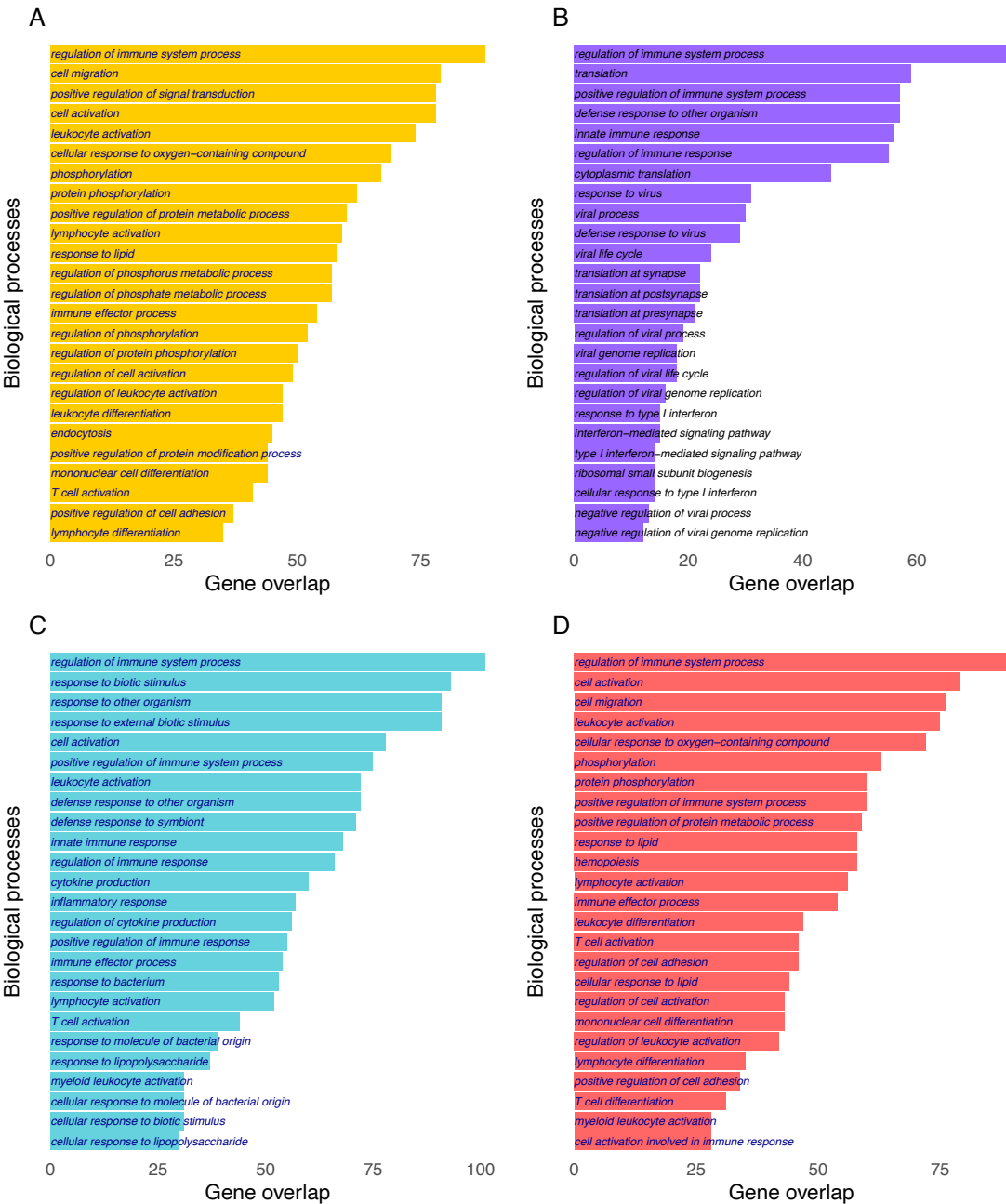


Figure 1 TWAS Volcano plot. A) Severe COVID-19, B) RSV-LRTI, C) PTB D) COVID-19 Severity. Red - upregulated, Blue - down regulated (P value <0.05, log2 Fold Change > 0).

166



167

168

169

170

Figure 2 Gene ontology term for biological process for top 500 genes. A) Severe COVID-19 B) RSV-LRTI C) PTB D) COVID-19 severity.

Severity of SARS-CoV-2 infection

In order to determine transcriptional responses that distinguish mild/asymptomatic SARS-CoV-2 infection from severe COVID-19, children hospitalised with COVID-19 were compared with seropositive DCHS children. We identified 163 upregulated and 183 down downregulated genes at $FDR < 0.05$ and \log_2 fold change > 1 see supplementary table S1. The pathways identified as enriched include regulation of immune system, hemopoieses and lymphocyte activation (see Figure 2D and supplementary table S2).

Weighted Gene Co-expression Networks Analysis of LRTI

The WGCNA analysis identified 46 significant modules including 22 with severe COVID-19, 22 with RSV-LRTI and 20 with PTB when compared with healthy controls ($p < 0.05$). Modules 10, 29, 22, 28 and 15 were downregulated and modules 32, 7, 19, 26 and 12 upregulated across LRTIs. The distribution of Eigengenes vs LRTI is shown in Figure 3A and Supplementary Table S3. The distribution of the relationship between the modules is represented as a dendrogram (Supplementary Figure 1) and genes per module are shown in Supplementary Table S3. The correlation of modules with COVID-19, RSV-LRTI and PTB are shown in Figure 3B. Thirty modules showing correlation across LRTIs ($r > 0.25$) were identified, of which 10 modules were correlated with all LRTI, 6 were in common between COVID-19 and RSV-LRTI, and 6 between COVID-19 and PTB (see Table 2 and Supplementary Fig 3). There were 4 modules specific to RSV-LRTI and 2 were specific to PTB.

The gene list in each module was used to generate a network using GeneMANIA with 10 additional interactors for biological processes in Cytoscape. Network analyses were conducted to characterise the network properties including identifying hub genes based on degree of connectivity. The top five hub genes for modules are shown in Table 2. The network connectivity degree distribution for

194 each module is provided in Supplementary Table S4. The Cytoscape session is also provided as
 195 Supplementary file 1.

196 The GO terms enrichment for modules which showed Pearson correlation of $r > 0.25$ with specific
 197 LRTI is in Supplementary Table S5. Further, redundant gene ontology was removed based on
 198 similarity matrix of GO terms using rrvgo R package. For biological process visualisation for all
 199 other modules see Supplementary Figure 4.

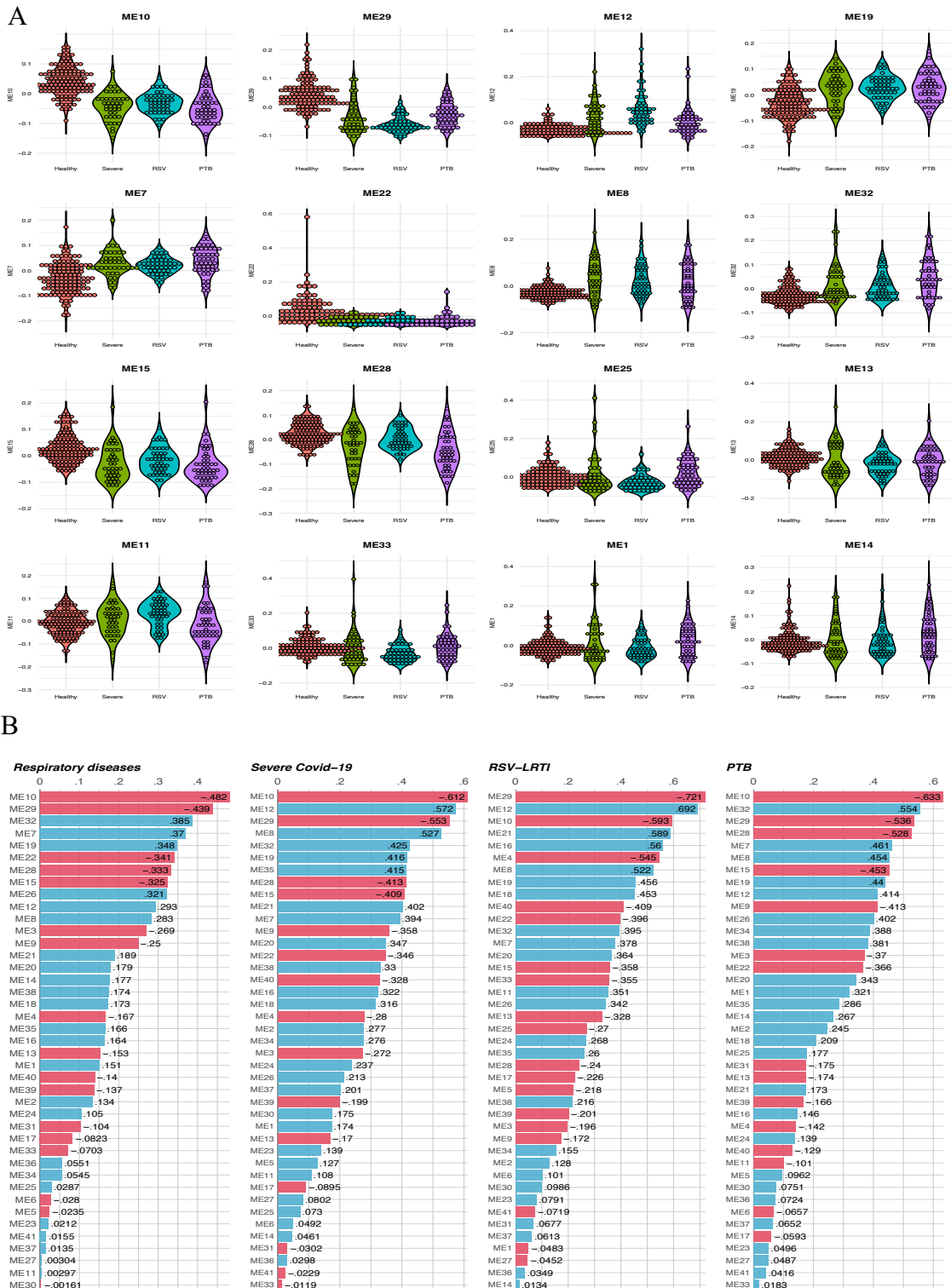


Figure 3. WGCNA analysis for respiratory infections and module correlation. A) Distribution of significant modules per respiratory infection (x-axis module eigengene vs y-axis respiratory infection), B) Correlation of Eigengene with respiratory infection.

205 Table 2 WGCNA modules correlated with respiratory infections at Pearson correlation $r > 0.25$ and $p < 0.05$.

Name	Total	Element	Top gene ontology	Top five hub genes
COVID19 PTB RSV- LRTI	10	ME7	Olfactory receptor activity and telomere maintenance	<i>OPHN1, PARD6A, ACADS, PMM1</i> and <i>VPS72</i>
		ME15	Adaptive immune response and granzyme-mediated programmed cell death	<i>TBX21, CCL5, GZMA, IL2RB</i> and <i>SH2D2A</i>
		ME29	Negative regulation of apoptosis	<i>AOC3, AMPD2, SGK1, DPEP2</i> and <i>TIGD3</i>
		ME22	Macrophage differentiation and cellular response to oxygen level	<i>CCR3, PIK3R6, CLC, PTGDR2</i> and <i>P2RY2</i>
		ME32	Eukaryotic translation initiation factor 4F complex and lymphocyte count	<i>STX18, PARP4, RASSF1, BLCAP</i> and <i>SAV1</i>
		ME10	Cytosolic transport and <i>TNFR2</i>	<i>TRIM28, MAPK3, P4HTM, ACTR1B</i> and <i>CNNM3</i>
		ME19	Viral transcription, aerobic respiration	<i>POLR2G, POLR2J, PSMB3, COX8A</i> and <i>NEDD8</i>
		ME12	Regulation of cell cycle	<i>CDK1, CCNB1, PLK1, MCM2</i> and <i>CDC6</i>
		ME8	B cell activation	<i>CD79A, BLNK, VPREB3, FCRLA</i> and <i>MS4A1</i>
		ME28	Adaptive immune response and T cell activation	<i>CD3E, LCK, CD3D, FYN</i> and <i>CD2</i>
COVID19 RSV- LRTI	6	ME18	Regulation of viral process and response to type I interferon	<i>STAT2, IRF9, STAT1, ISG15</i> and <i>IFIT3</i>
		ME16	RNA processes	<i>ABCE1, XPO1, MYC, IARS1</i> and <i>DHX15</i>
		ME4	Ribosomal biogenesis and leukocyte migration	<i>RGL2, TSEN34, MYC, SIRT7</i> and <i>FAM53C</i>
		ME21	Chromatin remodelling and hematopoietic stem cell differentiation	<i>MYC, PRPF8, TRIM28, TP53</i> and <i>FUS</i>
		ME24	Adaptive immune response and positive regulation of type I hypersensitivity	<i>HSP90B1, HSPA5, STT3A, PPIB</i> and <i>RPN1</i>
		ME40	Oxidative phosphorylation (mitochondrial respiratory chain complex)	<i>NDUFS4, NDUFS3, NDUF49, COX6B1</i> and <i>NDUFV2</i>
COVID19 PTB	6	ME35	Urea metabolic process	<i>IL1R2, PYGL, ITPKC, MTARC1</i> and <i>SDC4</i>
		ME3	Ribosomal biogenesis and viral gene expression	<i>RPL6, RPL37, RPS5, RPL35</i> and <i>RPL9</i>
		ME2	Active transmembrane transport	<i>STAC2, CDH3, PHLDB1, HAO1</i> and <i>SLC26A4</i>
		ME34	Antibacterial humoral response and regulation of cytokine production	<i>ELANE, CEACAM8, AZU1, CTSG</i> and <i>CEBPE</i>
		ME9	T cell differentiation and adaptive immune response	<i>ITK, LCK, CD3E, CD3D</i> and <i>CD3G</i>
		ME38	Positive regulation of carbohydrate metabolic process	<i>PIK3R1, INSR, IRS2, GRB10</i> and <i>ZBTB16</i>
PTB RSV- LRTI	2	ME26	Defence response to another organism, interferon-gamma and cell killing	<i>TAP1, STAT1, PSMB8, GBP1</i> and <i>PSMB9</i>
		ME20	Lipid catabolic process and Regulation of immune responses	<i>HEXB, CD14, FCER1G, GRN</i> and <i>LY96</i>
RSV- LRTI	4	ME25	Blood coagulation and haemostasis	<i>ITGB5, VCL, GP1BA, ITGB3</i> and <i>PF4</i>
		ME13	Antigen presenting -positive regulation of leukocyte mediated cytotoxicity	<i>UBC, ARPC1B, ARPC3, ARPC1A</i> and <i>GNAI2</i>
		ME11	rRNA processes and Mitochondrial gene expression	<i>PSMD14, CCT2, RFC4, CCT4</i> and <i>PRIM1</i>
		ME33	Autophagosome and viral process	<i>UBC, ULK1, MAPK14, RAB5B</i> and <i>TSG101</i>
PTB	2	ME1	Immune response regulation and Neutrophil degranulation	<i>HDAC1, PPP4R1, IFNGR2, ATP6V1B2</i> and <i>PRKCD</i>
		ME14	Regulation of defence response	<i>MYD88, CASP1, IRF9, IRF2</i> and <i>GBP2</i>

Cell population differences associated with LRTI

To determine cell type composition differences in peripheral blood between healthy controls and hospitalised subjects with LRTI due to different pathogens, blood cell type proportions were estimated with xCell2 2.0 generated with the ImmuneCompendium.xCell2Ref reference panel. Significant cell type composition differences were identified between healthy controls and hospitalised LRTI groups: 23 for severe COVID-19, 16 for RSV-LRTI and 21 for PTB ($p < 0.05$) (see Fig 4). To determine cell type composition difference between LRTIs we conducted t-tests as shown in Figure 5B. There was no difference in cell composition between healthy controls and those with mild/asymptomatic COVID-19. When the different hospitalised LRTI groups were compared with each other, several differences in cell composition were observed ($p < 0.05$). These included T cells (lower in severe COVID-19 vs PTB), non-classical monocytes (severe COVID-19 vs RSV-LRTI and RSV-LRTI and PTB) and myeloid cells (RSV-LRTI vs PTB). PTB also showed depletion of central memory CD8⁺ T Cells and overexpression of granulocytes compared to RSV-LRTI (see Supplementary Fig 5).

Seven cell types showed differences with healthy controls across all LRTIs including: Macrophages, transitional memory CD8⁺ T cells (CD8⁺ T_{tm}, T cells, Central memory CD8⁺ alpha-beta T cells, basophils, myeloid cells and naive thymus-derived CD8⁺ alpha-beta T cells. Neutrophils and class switched memory B cells showed significant changes for RSV-LRTI and PTB compared to the healthy controls but not for severe COVID-19. Disease specific unique cell type proportion changes were identified for severe COVID-19 as shown in Figure 5. The details are provided in Supplementary Table S6 and Supplementary Fig 6.

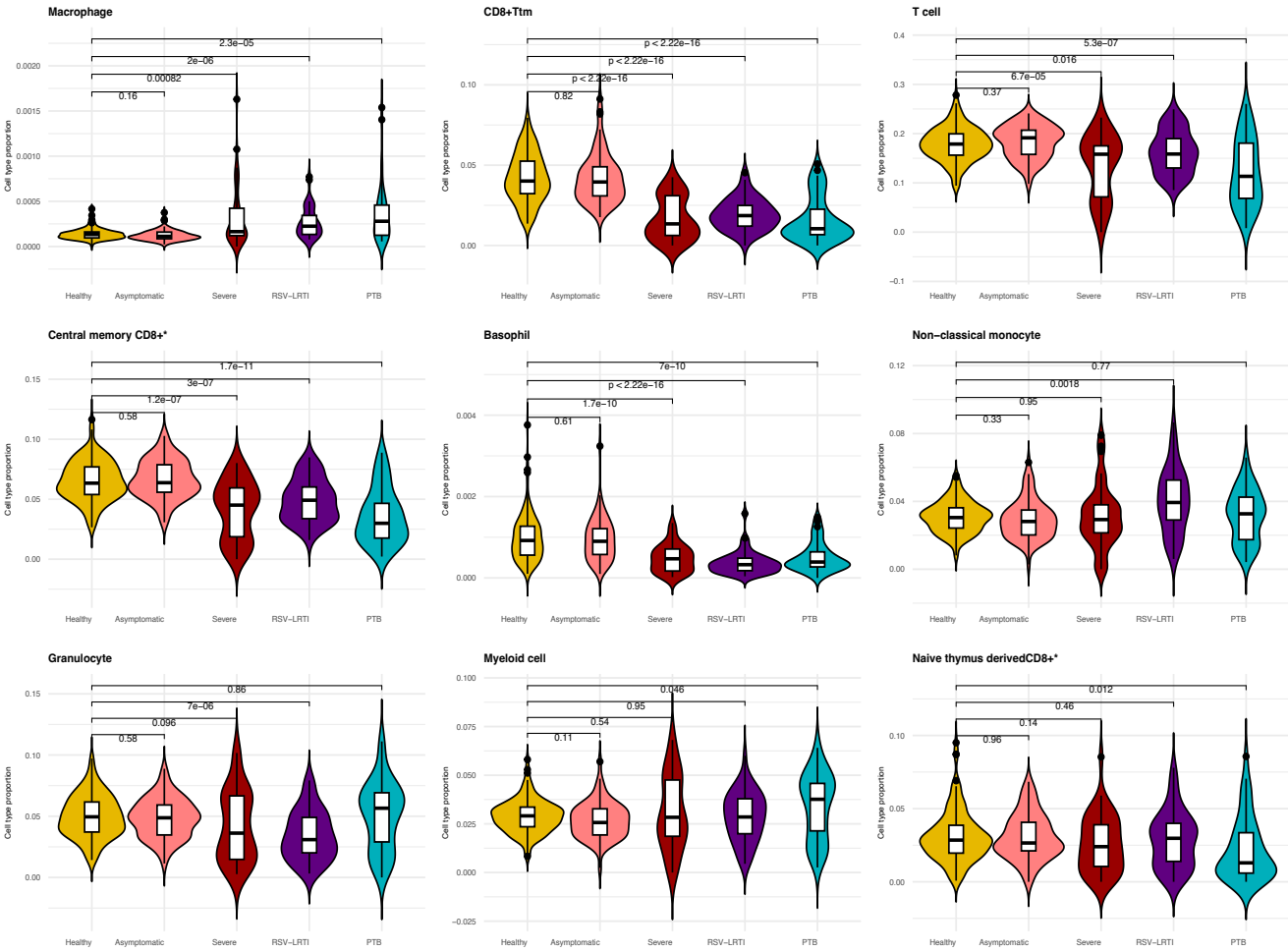


Figure 4 Differences in the proportions of immune cells in respiratory infections comparing healthy controls vs different LRTI groups. It shows the comparison of the five top cell types for LRTI and cell types uniquely different for RSV-LRTI and PTB.

Predictors of severe LRTI

To identify genes that represent biomarkers for each hospitalised LRTI, the normalized counts of the top 1000 significantly differentially expressed genes with respect to healthy controls were used and machine learning algorithms applied to identify the most informative genes. Ninety-three genes were identified as biomarkers for severe (hospitalised) COVID-19, 110 for RSV-LRTI and 95 for PTB as shown in Figure 5 and Supplementary Table S7.

Some genes were able to discriminate specific LRTIs from healthy controls including Severe COVID-19 (23), RSV-LRTI (74), PTB (37) and asymptomatic COVID-19 from severe COVID-19 (COVID-19 severity) (N=25) as shown in the Supplementary Figure 8. There were 10 genes that discriminated healthy controls from any LRTI including *IL16*, *LTK*, *IGIP*, *IGF2BP3*, *CBX7*, *KCTD7*, *FCERIA*, *TRAF1*, *RORC* and *SLC4A10*. See details of shared predictor genes amongst the LRTI groups in Supplementary Table S7.

Drug target lookup for genes associated with LRTI

To determine potentially therapeutic targets from DEGs associated with each LRTI, a look-up was undertaken for overlap with known druggability score generated by drugnomeAI. We identified 689, 159 and 849 genes for COVID-19, RSV-LRTI and PTB respectively with Tclin (approved drug targets) drugnomeAI score >90, as shown in Supplementary Table S8. For availability of drug and new therapeutic options we examined our predictors for availability of drugs as shown in Supplementary Table S9.

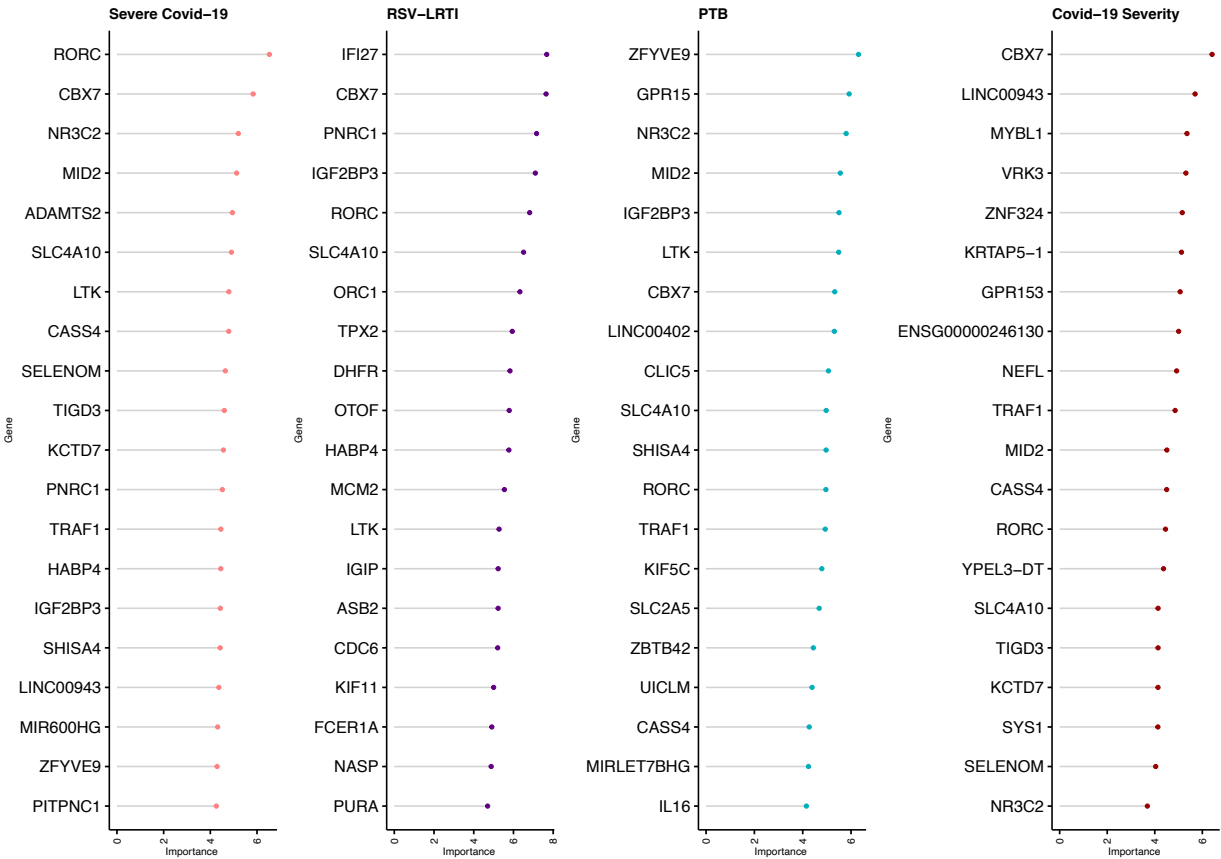


Figure 5 Top 20 gene severity predictors of LRTI for different etiologies based on mean importance. See shared predictors in Supplementary Fig 7.

Discussion

The transcriptional landscape of peripheral blood in response to viral and bacterial infections exhibits age-dependent variation, with implications for disease severity and immune regulation. In adults, SARS-CoV-2 infection has been studied extensively and elicits a robust transcriptional response characterized by upregulation of neutrophil activation markers, inflammatory cytokines, and interferon-stimulated genes (ISGs), alongside suppression of adaptive immune pathways and lymphocyte-associated transcripts^{41,42}. Children infected with SARS-CoV-2 typically exhibit mild or asymptomatic disease, with transcriptomic profiles showing restrained inflammatory responses and lower expression of viral entry receptors such as *ACE2* and *TMPRSS2*⁴³. However studies of the transcriptional responses to SARS-CoV-2 infection in children are extremely limited, focussing mainly on adolescents⁴⁴. In this study, for the first time, we report genome-wide assessment of transcriptional responses of children hospitalized with one of three LRTIs (COVID-19, RSV-LRTI, PTB), compared to healthy children in a birth cohort from a low- and middle-income African setting. We identify 4500 genes related to hospitalized COVID-19 and known signature genes for RSV-LRTI and for PTB. Unique and shared pathways and gene modules were characterised between LRTIs, along with unique signatures for each of the LRTIs.

COVID-19 related genes were enriched for immune system, neutrophil degranulation and interferon gamma signalling as previously reported in other studies in adults. Neutrophil degranulation has been previously correlated with COVID severity⁴⁵ and excess neutrophil degranulation is associated with tissue damage⁴⁶. The top upregulated genes included known genes responsible for immune responses, such as Interferon alpha-inducible protein 27 (*IFI27*) which is known to be an early predictor for COVID-19 outcome⁴⁷. Many studies have shown reduced

ribosomal protein expression and immune suppression associated with persistence of COVID-19 infection⁴⁸. Massoni *et al*³ have discussed immune dysregulation and exhaustion as a hallmark of COVID-19 where adaptive immune responses are highly heterogeneous. Thus, at an early phase of infection, type I IFN activity as an anti-viral response is important in the development of both adaptive and innate immunity.

RSV-LRTI upregulated genes include *OTOF*⁴⁹, *SIGLEC1*^{50,51}, *USP18*⁵² and *ISG15*⁵³. These genes were enriched for pathways including response to other organisms, regulation of viral life cycle, translational and interferon gamma signalling.

For PTB, we identified genes including *MMP8* and *MMP9* which are known to be associated with TB disease, by degradation of extracellular matrices^{54,55,56}. *DEFA1*, *DEFA1B*, *DEFA3* and *DEFA4* are a known cluster of genes in the PTB defence response pathway. The expression of *LTF* is also known to be an important biomarker for PTB disease^{57,58}. PTB specific markers such as *NCR3*, *CR2*, *CD28*, *IL10RA* and *GPR183* are functionally related to immune response, where *NCR3* stimulates NK cytotoxicity and *CR2* is involved in lymphocyte activation. These findings may contribute to understanding host responses in children in PTB and to strengthening diagnostic possibilities.

Using *WGCNA* co-expression analysis, we identified four RSV-LRTI specific modules: ME11 (translation and aerobic respiration), ME13 (antigen processing and T-cell mediated cytotoxicity), ME25 (coagulation and positive regulation of leukocyte) and ME33 (autophagy, viral processing and negative regulation of ferroptosis). A further two modules were specific to PTB: ME1 (immune response regulating signalling pathway and leukocyte differentiation) and ME14 (regulation of immune and defence response and cytokine production) (see Supplementary Fig 4).

While no modules were identified as specific to COVID-19, 22 modules were shared between COVID-19 and one or more LRTI, reflecting the seriousness of SARS-CoV-2 infection. Ten shared modules were identified across all LRTIs (Table 2) including module 10, which is associated with endosomes⁵⁹ and contains the hub gene *TNFR2*, known to be linked with immune dysregulation in severe COVID-19⁶⁰. In addition, module 10 contains many key hub genes known to be associated with COVID-19 severity including *TRIM28* (265 degree), *P4HTM* (245), *ACTR1B* (244), *CNNM3* (243), and *VPS51* (238). *TRIM28* is known to regulate SARS-CoV-2 entry by targeting *ACE2*⁶¹, suppressing antiviral immunity⁶² and is linked with COVID-19 severity⁶³. *P4HTM* is known to play a role in adaptation to hypoxia and energy response and is linked with hypoventilation⁶⁴.

Other shared modules include: Module 22 the hub gene *CCR3* (C-C motif chemokine receptor 3) regulates cell migration and inflammatory responses by acting as a receptor for various CC chemokines such as eotaxin, and is a susceptibility gene for severe COVID-19⁶⁵. Module 28 was related to adaptive immune response and T-cell activation; with hub genes including *CD3E* involved in T-cell signalling to detect and clear pathogens. Module 7 was enriched for sensory perception such as olfactory dysfunction, a known symptom in COVID-19⁶⁶. Module 15 was related to T-cell differentiation and adaptive immunity where hub gene *TBX21* is a transcription factor that modulates innate immunity by regulating the expression of *TLR2*⁶⁷. *GZMA* and *GZMB* play a role in immune response during respiratory infection⁶⁸. *IFNG* is involved in clearing viral infection⁶⁹.

A further six modules were shared between COVID-19 and PTB including module 34 which was enriched for antimicrobial humoral responses (*DEFA1*, *DEFA3*, *RNASE3*, *BPI*, *PGLYRP1*, *CAMP*, *AZUI*, *ELANE* and *LTF*) and neutrophil degranulation⁷⁰ in the Reactome database (*DEFA1*,

325 *ORM1, ORM2, RNASE3, ATP8B4, STBD1, BPI, PGLYRP1, TCN1, MS4A3, ABCA13, CLEC5A,*
326 *CAMP, AZU1, CPNE3, CEACAM8, ELANE, CEACAM6, CRISP3, LTF, PLD1, MMP8, CHIT1,*
327 *LCN2, OLR1 and SLC2A).* The hub gene *ELANE* encodes a serine protease secreted by neutrophils
328 that is known to regulate the function of natural killer cells, monocytes and granulocytes and is
329 essential for neutrophils in fighting infections^{71,72}. Neutrophil activation is characteristic of severe
330 COVID-19⁷³ and shared with other inflammatory states⁷⁴. Module 26, identified as shared between
331 PTB and RSV-LRTI, includes the hub gene *TAP1* which is known for its antiviral activity through
332 Type I interferon production⁷⁵. Other hub genes include *STAT, PSMB8, GBP1, PSMB9, HLA-E,*
333 *GBP5, HLA-F, GBP2, IRF9, APOL3* and *CASP1* which are also known be associated with
334 COVID-19⁷⁶. The detailed enrichment for GO terms are provided in Supplementary Table S5 and
335 Supplementary Fig 4.

336 Cell proportion estimation showed that in children hospitalised with COVID-19 there was
337 depletion of macrophages and monocytes compared to healthy controls. In contrast, in children
338 hospitalised with RSV-LRTI, increased proportions of regulatory T-cells and macrophages, and a
339 depletion of T-cells and class switched memory B-cells were observed. Similarly, for PTB, there
340 was an increase in macrophages, monocytes and neutrophils, and a depletion of T-cells and CD8+
341 alpha-beta T-cells, and cytotoxic NK cells (Fig 4). The depletion of T and B cells is a key feature
342 of COVID-19 severity⁷⁷. T-cell immunity is essential to control PTB⁷⁸.

343 We identified 247 genes that predicted the severity of LRTI. Ten were common among LRTIs.
344 *IL16* is involved in pro-inflammatory responses to activate T-cells and the production of
345 cytokines⁷⁹. Five genes could discriminate hospitalised children with LRTI including: *PITPNC1,*
346 *TPX2, LARPI, HABP4* and *SMIM10L2A*. *PITPNC1* is known for pulmonary function and
347 asthma⁸⁰. Five genes, including *PAFAH2, LINC02915, CLSPN, EIF4G1* and *IFI27*, were

predictors of both COVID-19 and RSV-LRTI hospitalization. *PAFAH2* is known to be associated with pulmonary micro-thromboses linked with LRTI severity^{81,82}. The top COVID-19 predictor, *RORC*, is a key regulator of cellular differentiation, immunity and glucose metabolism. *CBX7* is part of the Polycomb complex required for transcriptional repression of many genes and cancer progression⁸³ and is functionally linked with lymphocyte, monocyte and neutrophil counts. *ZFVE9* is known to be predictive of active TB⁸⁴. The *ADAMTS2* is metalloprotease that processes extracellular matrix is implicated in tissue damage⁸⁵ and is a marker for COVID-19 severity across disease conditions⁸⁶.

Assessing the potential druggability of differentially expressed genes can help in prioritizing drug targets. Amongst the DEGs for LRTIs, known approved drug targets (TClin) were identified including: *KCND3*, *CACNA1E*, *GABRG2*, *CHRNA5*, *KCND1* and *ADRB2* for severe COVID-19; *GABRG2*, *KCND1*, *CA12*, *CACNA1A*, *IMPDH2* and *PDE1B* for RSV-LRTI; *CACNA1E*, *GABRG2*, *KCNK3*, *CHRNA5* and *CHRNA2* for PTB as shown in Supplementary Table S8.

Interestingly, the top predictors of severity were not previously identified as drug targets, including *CBX7*, *MYBL1*, *VRK3*, *ZNF324*, *KRTAP5-1* and *GPR153*. In the top PTB predictors, *NR3C2* and *GPR15* have high scores for Tclin but the top predictors, *MID2* and *ZFYVE9*, have not previously been identified as drug targets showing opportunity for drug target prioritization for this population. For RSV-LRTI, except for *RORC*, most top predictors (*IFI27*, *CBX7*, *PNRC1* and *IGF2BP3*) have not previously been targeted for drug development (Supplementary Table S9).

One of the strengths of our study is the assessment of hospitalised children with one of the three major LRTIs in children in LMICs and comparison with healthy children using datasets generated from a similar genetic background. Many known signature-genes identified for COVID-19 (*IFI27*, *OLFM4*), RSV-LRTI (*SIGLEC1*, *ISG15*, *IFI44*) and PTB (*MMP8*, *MMP9*, *DEFA1*, *DEFA1B*,

DEFA3 and *DEFA4*) are known to be associated with progressive severity⁸⁷, showing the reproducibility of our findings. A limitation is that the DCHS children were older than children with LRTI, but we used age as a covariate to overcome this confounding effect.

From our transcriptomic analysis of children with LRTIs due to three different aetiologies, we have identified novel data providing key immune response related genes associated with severity for children hospitalised with COVID-19, RSV-LRTI and PTB in African children. These genes can be used for baseline characterization, as predictive markers for respiratory infection severity and as potential therapeutic targets.

Data availability

Supplementary data and summary statistics for transcriptome wide association analyses are available from: DOI <https://doi.org/10.5258/SOTON/D3587>.

An anonymised, de-identified version with data can be made available on request. All requests should be directed to Prof Heather Zar, DCHS Study Principal Investigator.

Code availability

The custom code used to generate graphics is available at GitHub repository: https://github.com/negusse2025/respiratory_infections.git.

Acknowledgements

Funding, participants/ families and staff. The some of the graphic illustrations for graphic abstract were accessed from NIH BIOART, including TB (<https://bioart.niaid.nih.gov/bioart/527>), child (<https://bioart.niaid.nih.gov/bioart/75>) and SARS-CoV-2 (<https://bioart.niaid.nih.gov/bioart/464>).

Funding

HJZ reports grants from UK NIHR (GEC111), Wellcome Biomedical resources grant (221372/Z/20/Z), Wellcome Trust Centre for Infectious Disease Research in Africa (CIDRI), Bill & Melinda Gates Foundation USA, (OPP1017641, OPP1017579) and NIH H3 Africa (U54HG009824, U01AI110466)]. HZ is supported by the SA-MRC. NTK is supported by the National Institute for Health and Care Research through the NIHR Southampton Biomedical Research Centre. Additionally, both NTK and JHW received supported from University of Southampton's Global Partnership Award University of Southampton.

Author information

H.J.Z., M.P.K., M.B., N.T.K., D.B. and J.W.H. contributed to conceptualisation. N.T.K., L.W., H.J.Z. and J.W.H. performed data curation. N.T.K., E.K. and J.W.H. carried out formal analysis. N.T.K., M.J., E.K., M.B., D.G., M.P.K. and J.W.H. provided methodology. H.J.Z performed project administration. N.T.K., H.J.Z. and J.W.H. performed writing—original draft. N.T.K., C.C., D.B., E.K., L.W., M.B., M.J., M.P.K., H.J.Z. and J.W.H. contributed to writing—review, editing and final approval.

References

1. Mazur, N. I., Caballero, M. T. & Nunes, M. C. Severe respiratory syncytial virus infection in children: burden, management, and emerging therapies. *The Lancet* **404**, 1143–1156 (2024).
2. De Souza, T. H., Nadal, J. A., Nogueira, R. J. N., Pereira, R. M. & Brandão, M. B. Clinical manifestations of children with COVID-19: A systematic review. *Pediatr. Pulmonol.* **55**, 1892–1899 (2020).
3. Mazzoni, A., Salvati, L., Maggi, L., Annunziato, F. & Cosmi, L. Hallmarks of immune response in COVID-19: Exploring dysregulation and exhaustion. *Semin. Immunol.* **55**, 101508 (2021).
4. Sun, Y.-K. *et al.* Severe pediatric COVID-19: a review from the clinical and immunopathophysiological perspectives. *World J. Pediatr.* **20**, 307–324 (2024).
5. Soares-Schanoski, A. *et al.* Asymptomatic SARS-CoV-2 Infection Is Associated With Higher Levels of Serum IL-17C, Matrix Metalloproteinase 10 and Fibroblast Growth Factors Than Mild Symptomatic COVID-19. *Front. Immunol.* **13**, 821730 (2022).
6. Khoury, D. S. *et al.* Neutralizing antibody levels are highly predictive of immune protection from symptomatic SARS-CoV-2 infection. *Nat. Med.* **27**, 1205–1211 (2021).
7. Legebeke, J. *et al.* Evaluating the Immune Response in Treatment-Naive Hospitalised Patients With Influenza and COVID-19. *Front. Immunol.* **13**, 853265 (2022).
8. Bibert, S. *et al.* Transcriptomic Signature Differences Between SARS-CoV-2 and Influenza Virus Infected Patients. *Front. Immunol.* **12**, 666163 (2021).
9. Penrice-Randal, R. *et al.* Blood gene expression predicts intensive care unit admission in hospitalised patients with COVID-19. *Front. Immunol.* **13**, 988685 (2022).
10. Loy, C. J. *et al.* Nucleic acid biomarkers of immune response and cell and tissue damage in children with COVID-19 and MIS-C. *Cell Rep. Med.* **4**, 101034 (2023).

- 436 11. Patnaik, S. *et al.* RNAseq-based transcriptomics of treatment-naïve multi-inflammatory
437 syndrome in children (MIS-C) demonstrates predominant activation of matrisome, innate and
438 humoral immune pathways. *Rheumatol. Int.* **44**, 1445–1454 (2023).
- 439 12. Yang, Z. *et al.* Recent progress in tuberculosis diagnosis: insights into blood-based
440 biomarkers and emerging technologies. *Front. Cell. Infect. Microbiol.* **15**, 1567592 (2025).
- 441 13. Theuretzbacher, U., Jumde, R. P., Hennessy, A., Cohn, J. & Piddock, L. J. V. Global health
442 perspectives on antibacterial drug discovery and the preclinical pipeline. *Nat. Rev. Microbiol.*
443 <https://doi.org/10.1038/s41579-025-01167-w> (2025) doi:10.1038/s41579-025-01167-w.
- 444 14. Farhat, M. *et al.* Drug-resistant tuberculosis: a persistent global health concern. *Nat. Rev.*
445 *Microbiol.* **22**, 617–635 (2024).
- 446 15. Fossati, A. *et al.* Plasma proteomics for novel biomarker discovery in childhood
447 tuberculosis. Preprint at <https://doi.org/10.1101/2024.12.05.24318340> (2024).
- 448 16. Gygi, J. P. *et al.* Integrated longitudinal multiomics study identifies immune programs
449 associated with acute COVID-19 severity and mortality. *J. Clin. Invest.* **134**, e176640 (2024).
- 450 17. Zhang, B. & Horvath, S. A General Framework for Weighted Gene Co-Expression
451 Network Analysis. *Stat. Appl. Genet. Mol. Biol.* **4**, (2005).
- 452 18. Investigating the early-life determinants of illness in Africa: the Drakenstein Child Health
453 Study.
- 454 19. Benede, N. *et al.* Distinct T cell polyfunctional profile in SARS-CoV-2 seronegative
455 children associated with endemic human coronavirus cross-reactivity. *iScience* **27**, 108728
456 (2024).
- 457 20. Zar, H. J. *et al.* Natural immunity and protection against variants in South African children
458 through five COVID-19 waves: A prospective study. *Int. J. Infect. Dis.* **150**, 107300 (2025).

- 459 21. Simon, Andrew. FastQC: A Quality Control Tool for High Throughput Sequence Data
460 [Online]. 2010 Available online at:
461 <http://www.bioinformatics.babraham.ac.uk/projects/fastqc/>.
- 462 22. Ewels, P., Magnusson, M., Lundin, S. & Käller, M. MultiQC: Summarize analysis results
463 for multiple tools and samples in a single report. *Bioinformatics* **32**, 3047–3048 (2016).
- 464 23. Dobin, A. *et al.* STAR: ultrafast universal RNA-seq aligner. *Bioinformatics* **29**, 15–21
465 (2013).
- 466 24. Patro, R., Duggal, G., Love, M. I., Irizarry, R. A. & Kingsford, C. Salmon: fast and bias-
467 aware quantification of transcript expression using dual-phase inference. *Nat. Methods* **14**, 417–
468 419 (2017).
- 469 25. Robinson, M. D., McCarthy, D. J. & Smyth, G. K. edgeR: A Bioconductor package for
470 differential expression analysis of digital gene expression data. *Bioinformatics* **26**, 139–140
471 (2009).
- 472 26. Robinson, M. D. & Oshlack, A. A scaling normalization method for differential expression
473 analysis of RNA-seq data. *Genome Biol.* **11**, R25 (2010).
- 474 27. Chen, X., Zhang, B., Wang, T., Bonni, A. & Zhao, G. Robust principal component analysis
475 for accurate outlier sample detection in RNA-Seq data. *BMC Bioinformatics* **21**, 269 (2020).
- 476 28. Ritchie, M. E. *et al.* limma powers differential expression analyses for RNA-sequencing
477 and microarray studies. *Nucleic Acids Res.* **43**, e47 (2015).
- 478 29. Chen, J., Bardes, E. E., Aronow, B. J. & Jegga, A. G. ToppGene Suite for gene list
479 enrichment analysis and candidate gene prioritization. *Nucleic Acids Res.* **37**, W305–W311
480 (2009).

- 481 30. Horvath, P. L. and S. WGCNA: an R package for weighted correlation network analysis.
482 *Oncol. Rep.* **11**, 515–522 (2004).
- 483 31. Lares, B. lares: Lean Analytics and Robust Exploration Sidekick. 2025 2025.
- 484 32. Warde-Farley, D. *et al.* The GeneMANIA prediction server: biological network integration
485 for gene prioritization and predicting gene function. *Nucleic Acids Res.* **38**, W214–W220
486 (2010).
- 487 33. Christmas, C., Rowan; Avila-Campillo, Iliana; Bolouri, Hamid; Schwikowski, Benno;
488 Anderson, Mark; Kelley, Ryan; Landys, Nerius; Workman, Chris; Ideker, Trey; Cerami, Ethan;
489 Sheridan, Rob; Bader, Gary D. ;. Sander. Cytoscape: a software environment for integrated
490 models of biomolecular interaction networks. *Am. Assoc. Cancer Res. Educ. Book* 12–16 (2005)
491 doi:10.1101/gr.1239303.metabolite.
- 492 34. Sayols, S. rrvgo: a Bioconductor package for interpreting lists of Gene Ontology terms.
493 *Open Access*.
- 494 35. Angel, A., Naom, L., Nabet-Levy, S. & Aran, D. xCell 2.0: Robust Algorithm for cell type
495 Proportion Estimation Predicts Response to Immune Checkpoint Blockade. Preprint at
496 <https://doi.org/10.1101/2024.09.06.611424> (2024).
- 497 36. Godec, J. *et al.* Compendium of Immune Signatures Identifies Conserved and Species-
498 Specific Biology in Response to Inflammation. *Immunity* **44**, 194–206 (2016).
- 499 37. Tarke, A. *et al.* Comprehensive analysis of T cell immunodominance and
500 immunoprevalence of SARS-CoV-2 epitopes in COVID-19 cases. *Cell Rep. Med.* **2**, 100204
501 (2021).
- 502 38. Kursa, M. B., Jankowski, A. & Rudnicki, W. R. Boruta – A System for Feature Selection.
503 *Fundam. Informaticae* **101**, 271–285 (2010).

- 504 39. Andy Liaw and Matthew Wiener. Classification and Regression by randomForest. *R News*
505 2, 18–22 (2002).
- 506 40. Raies, A. *et al.* DrugnomeAI is an ensemble machine-learning framework for predicting
507 druggability of candidate drug targets. *Commun. Biol.* **5**, 1291 (2022).
- 508 41. Schulte-Schrepping, J. *et al.* Severe COVID-19 Is Marked by a Dysregulated Myeloid Cell
509 Compartment. *Cell* **182**, 1419-1440.e23 (2020).
- 510 42. Legebeke, J. *et al.* Evaluating the Immune Response in Treatment-Naive Hospitalised
511 Patients With Influenza and COVID-19. *Front. Immunol.* **13**, 853265 (2022).
- 512 43. Pierce, C. A. *et al.* Immune responses to SARS-CoV-2 infection in hospitalized pediatric
513 and adult patients. *Sci. Transl. Med.* **12**, eabd5487 (2020).
- 514 44. Bando, S. Y. *et al.* Blood leukocyte transcriptional modules and differentially expressed
515 genes associated with disease severity and age in COVID-19 patients. *Sci. Rep.* **13**, 898 (2023).
- 516 45. Muralidharan, A., Wyatt, T. A. & Reid, S. P. SARS-CoV-2 Dysregulates Neutrophil
517 Degranulation and Reduces Lymphocyte Counts. *Biomedicines* **10**, 382 (2022).
- 518 46. Herro, R. & Grimes, H. L. The diverse roles of neutrophils from protection to pathogenesis.
519 *Nat. Immunol.* **25**, 2209–2219 (2024).
- 520 47. Shojaei, M. *et al.* IFI27 transcription is an early predictor for COVID-19 outcomes, a multi-
521 cohort observational study. *Front. Immunol.* **13**, 1060438 (2023).
- 522 48. Yang, B. *et al.* Clinical and molecular characteristics of COVID-19 patients with persistent
523 SARS-CoV-2 infection. *Nat. Commun.* **12**, 3501 (2021).
- 524 49. Ding, H. *et al.* Membrane Protein OTOF Is a Type I Interferon-Induced Entry Inhibitor of
525 HIV-1 in Macrophages. *mBio* **13**, e01738-22 (2022).

50. Jans, J. *et al.* Siglec-1 inhibits RSV-induced interferon gamma production by adult T cells in contrast to newborn T cells. *Eur. J. Immunol.* **48**, 621–631 (2018).
51. Herzog, S., Fragkou, P. C., Arneth, B. M., Mkhlof, S. & Skevaki, C. Myeloid CD169/Siglec1: An immunoregulatory biomarker in viral disease. *Front. Med.* **9**, 979373 (2022).
52. Hou, J. *et al.* USP18 positively regulates innate antiviral immunity by promoting K63-linked polyubiquitination of MAVS. *Nat. Commun.* **12**, 2970 (2021).
53. González-Sanz, R. *et al.* ISG15 Is Upregulated in Respiratory Syncytial Virus Infection and Reduces Virus Growth through Protein ISGylation. *J. Virol.* **90**, 3428–3438 (2016).
54. Ong, C. W. M. *et al.* Neutrophil-Derived MMP-8 Drives AMPK-Dependent Matrix Destruction in Human Pulmonary Tuberculosis. *PLOS Pathog.* **11**, e1004917 (2015).
55. Ugarte-Gil, C. A. *et al.* Induced Sputum MMP-1, -3 & -8 Concentrations during Treatment of Tuberculosis. *PLoS ONE* **8**, e61333 (2013).
56. Sathyamoorthy, T. *et al.* Membrane Type 1 Matrix Metalloproteinase Regulates Monocyte Migration and Collagen Destruction in Tuberculosis. *J. Immunol.* **195**, 882–891 (2015).
57. Shao, M. *et al.* Screening of potential biomarkers for distinguishing between latent and active tuberculosis in children using bioinformatics analysis. *Medicine (Baltimore)* **100**, e23207 (2021).
58. Datta, A., Gupta, D., Waryani, D. & C, G. P. D. Decoding differentially expressed genes to identify potential immunity associated biomarkers in Tuberculosis: An integrative bioinformatics approach. *Biochem. Biophys. Rep.* **40**, 101870 (2024).
59. Vale-Costa, S. & Amorim, M. Recycling Endosomes and Viral Infection. *Viruses* **8**, 64 (2016).

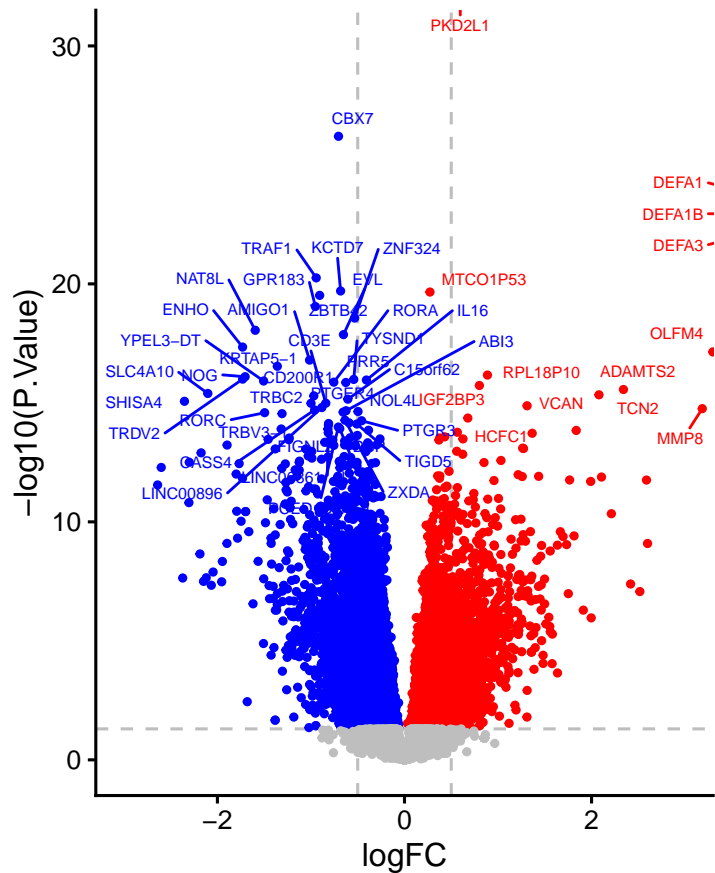
- 549 60. Ahmad, S. *et al.* The role of TNFR2+ Tregs in COVID-19: An overview and a potential
550 therapeutic strategy. *Life Sci.* **286**, 120063 (2021).
- 551 61. Wang, Y. *et al.* TRIM28 regulates SARS-CoV-2 cell entry by targeting ACE2. *Cell. Signal.*
552 **85**, 110064 (2021).
- 553 62. Ren, J. *et al.* TRIM28-mediated nucleocapsid protein SUMOylation enhances SARS-CoV-
554 2 virulence. *Nat. Commun.* **15**, 244 (2024).
- 555 63. Tavakoli, R. *et al.* Comparing the expression levels of tripartite motif containing 28 in mild
556 and severe COVID-19 infection. *Virol. J.* **19**, 156 (2022).
- 557 64. Hay, E. *et al.* Biallelic P4HTM variants associated with HIDEA syndrome and
558 mitochondrial respiratory chain complex I deficiency. *Eur. J. Hum. Genet.* **29**, 1536–1541
559 (2021).
- 560 65. Sun, Z., Pan, L., Tian, A. & Chen, P. Critically-ill COVID-19 susceptibility gene CCR3
561 shows natural selection in sub-Saharan Africans. *Infect. Genet. Evol.* **121**, 105594 (2024).
- 562 66. Othman, B. A. *et al.* Olfactory dysfunction as a post-infectious symptom of SARS-CoV-2
563 infection. *Ann. Med. Surg.* **75**, (2022).
- 564 67. Woo, C. H., Shin, S. G., Koh, S. H. & Lim, J. H. TBX 21 participates in innate immune
565 response by regulating Toll-like receptor 2 expression in *S. treptococcus pneumoniae*
566 infections. *Mol. Oral Microbiol.* **29**, 233–243 (2014).
- 567 68. Loebbermann, J. *et al.* Regulatory T cells expressing granzyme B play a critical role in
568 controlling lung inflammation during acute viral infection. *Mucosal Immunol.* **5**, 161–172
569 (2012).
- 570 69. Eichinger, K. M. *et al.* Alveolar macrophages support interferon gamma-mediated viral
571 clearance in RSV-infected neonatal mice. *Respir. Res.* **16**, 122 (2015).

- 572 70. Zhang, F. *et al.* Neutrophil diversity and function in health and disease. *Signal Transduct.*
573 *Target. Ther.* **9**, 343 (2024).
- 574 71. Jia, W., Mao, Y., Luo, Q., Wu, J. & Guan, Q. Targeting neutrophil elastase is a promising
575 direction for future cancer treatment. *Discov. Oncol.* **15**, 167 (2024).
- 576 72. Tralau, T., Meyer-Hoffert, U., Schröder, J. & Wiedow, O. Human leukocyte elastase and
577 cathepsin G are specific inhibitors of C5a-dependent neutrophil enzyme release and chemotaxis.
578 *Exp. Dermatol.* **13**, 316–325 (2004).
- 579 73. Wang, X., Sanborn, M. A., Dai, Y. & Rehman, J. Temporal transcriptomic analysis using
580 TrendCatcher identifies early and persistent neutrophil activation in severe COVID-19. *JCI*
581 *Insight* **7**, e157255 (2022).
- 582 74. Schimke, L. F. *et al.* Severe COVID-19 Shares a Common Neutrophil Activation Signature
583 with Other Acute Inflammatory States. *Cells* **11**, 847 (2022).
- 584 75. Zhao, J. *et al.* Broadly Antiviral Activities of TAP1 through Activating the TBK1-IRF3-
585 Mediated Type I Interferon Production. *Int. J. Mol. Sci.* **22**, 4668 (2021).
- 586 76. Schmidt, N. *et al.* The SARS-CoV-2 RNA–protein interactome in infected human cells.
587 *Nat. Microbiol.* **6**, 339–353 (2020).
- 588 77. Ahern, D. J. *et al.* A blood atlas of COVID-19 defines hallmarks of disease severity and
589 specificity. *Cell* **185**, 916–938.e58 (2022).
- 590 78. Ogongo, P. *et al.* Tissue-resident-like CD4⁺ T cells secreting IL-17 control Mycobacterium
591 tuberculosis in the human lung. *J. Clin. Invest.* **131**, e142014 (2021).
- 592 79. Mathy, N. L. *et al.* Interleukin-16 stimulates the expression and production of pro-
593 inflammatory cytokines by human monocytes. (2000).

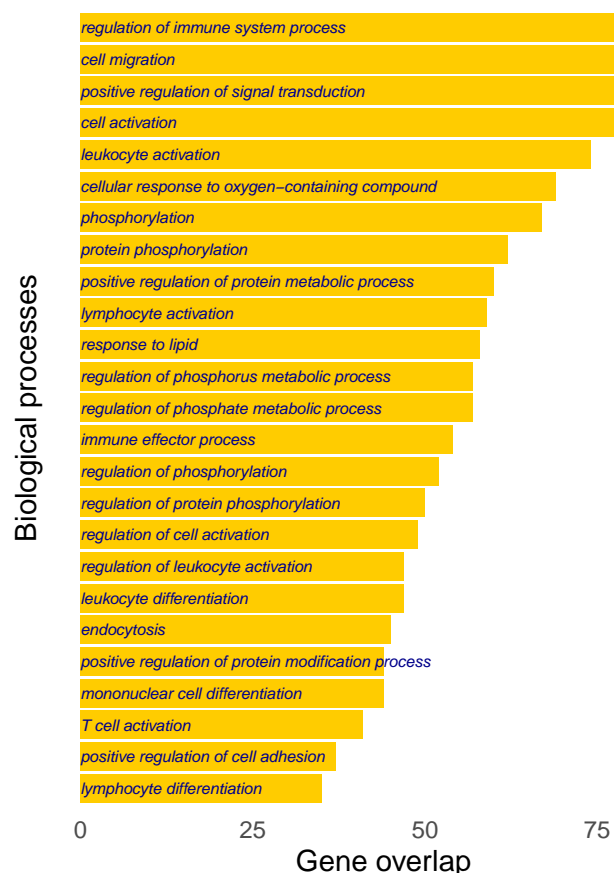
80. Yucesoy, B. *et al.* Genome-Wide Association Study Identifies Novel Loci Associated With Diisocyanate-Induced Occupational Asthma. *Toxicol. Sci.* **146**, 192–201 (2015).
81. Theoharides, T. C., Antonopoulou, S. & Demopoulos, C. A. Coronavirus 2019, Microthromboses, and Platelet Activating Factor. *Clin. Ther.* **42**, 1850–1852 (2020).
82. Demopoulos, C., Antonopoulou, S. & Theoharides, T. C. COVID -19, microthromboses, inflammation, and platelet activating factor. *BioFactors* **46**, 927–933 (2020).
83. Pallante, P., Forzati, F., Federico, A., Arra, C. & Fusco, A. Polycomb protein family member CBX7 plays a critical role in cancer progression.
84. Duffy, F. J. *et al.* Use of a Contained *Mycobacterium tuberculosis* Mouse Infection Model to Predict Active Disease and Containment in Humans. *J. Infect. Dis.* **225**, 1832–1840 (2022).
85. Loy, C. J. *et al.* Nucleic acid biomarkers of immune response and cell and tissue damage in children with COVID-19 and MIS-C. *Cell Rep. Med.* **4**, 101034 (2023).
86. Singh, M. S., Arun, P. P. S. & Ansari, M. A. Unveiling common markers in COVID-19: ADAMTS2, PCSK9, and OLAH emerged as key differential gene expression profiles in PBMCs across diverse disease conditions. *AIMS Mol. Sci.* **11**, 189–205 (2024).
87. Armignacco, R. *et al.* Whole blood transcriptome signature predicts severe forms of COVID-19: Results from the COVIDeF cohort study. *Funct. Integr. Genomics* **24**, 107 (2024).

614 Supplementary data

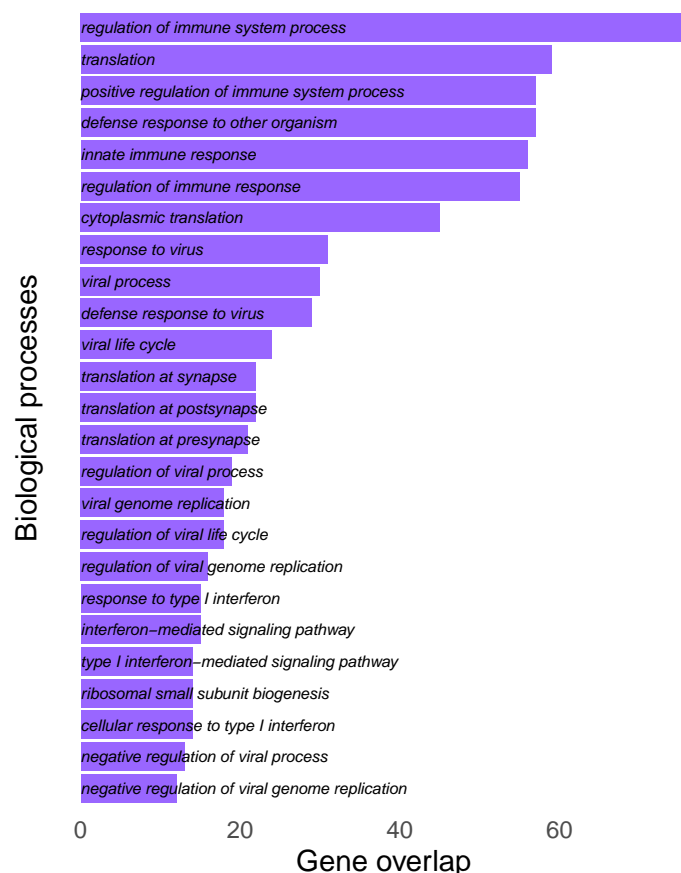
- 615 Supplementary Fig 1 Module dendrogram
- 616 Supplementary Fig 2 Distribution of genes per module
- 617 Supplementary Fig 3 Venn diagram shared modules between respiratory infections
- 618 Supplementary Fig 4 REVIGO biological process for correlated modules with LRTI
- 619 Supplementary Fig 5 Blood composition comparisons between LRTI
- 620 Supplementary Fig 6 Shared cell types
- 621 Supplementary Fig 7 Shared severity predictors for LRTI
- 622 Supplementary table S1 Respiratory infection TWAS FDR< 0.05
- 623 Supplementary table S2 Respiratory infection TWAS enrichment
- 624 Supplementary table S3 WGCNA module genes and eigengene
- 625 Supplementary table S4 Network degree distribution for module correlated to LRTI
- 626 Supplementary table S5 Enrichment for module correlated to LRTI
- 627 Supplementary Table S6 Cell type proportions
- 628 Supplementary table S7 severity predictors
- 629 Supplementary table S8 Drug target look-up
- 630 Supplementary table S9 Severity predictors and target prioritization
- 631 Supplementary file Modules_Network_analysis.cys.
- 632



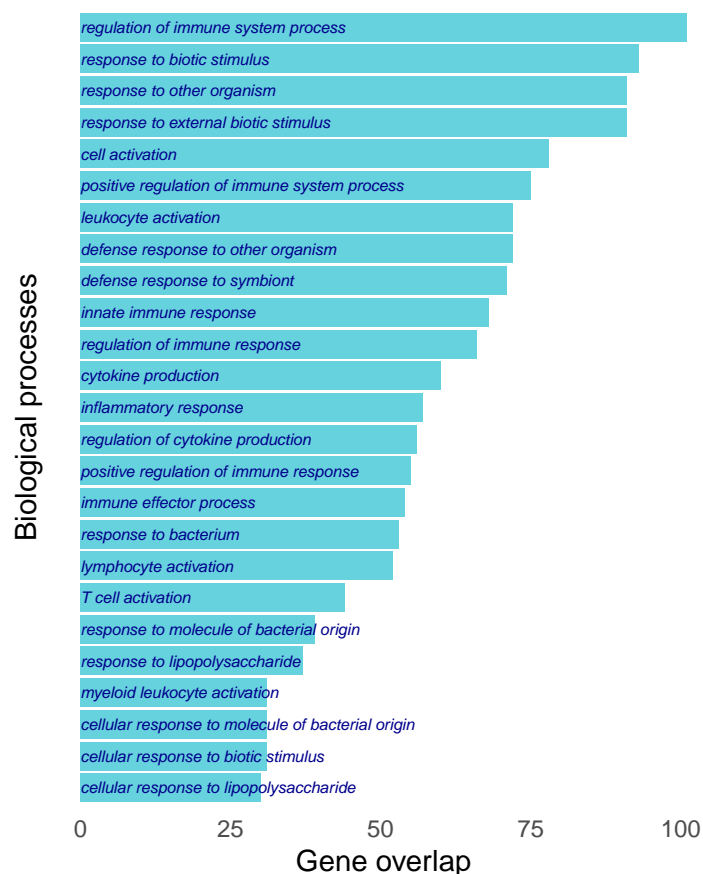
A



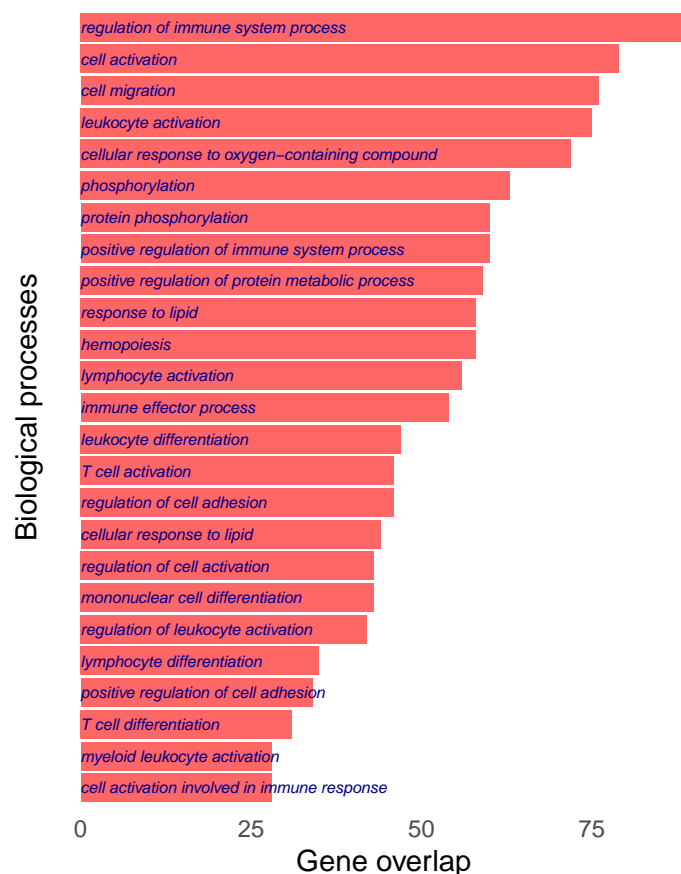
B



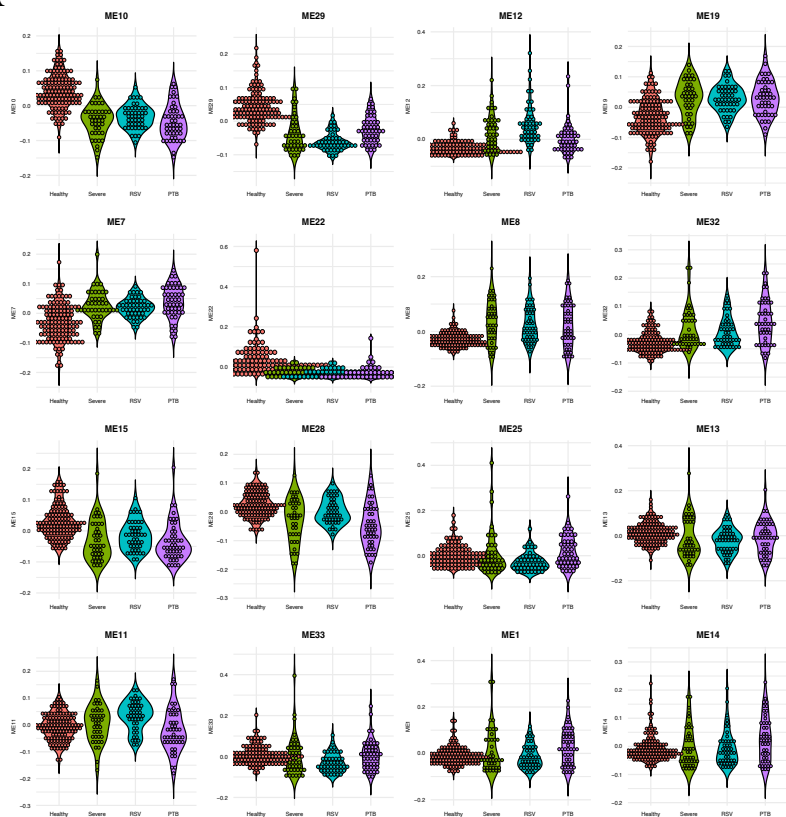
C



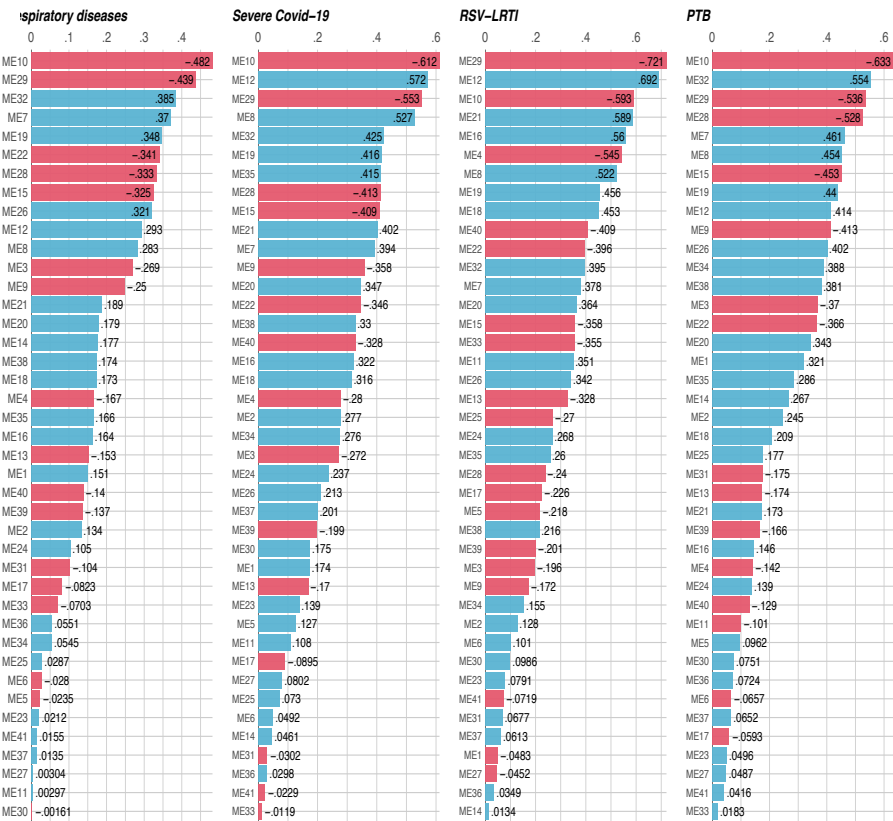
D

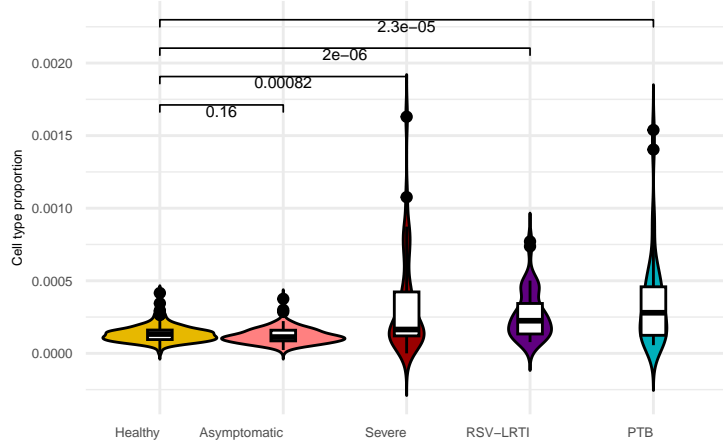
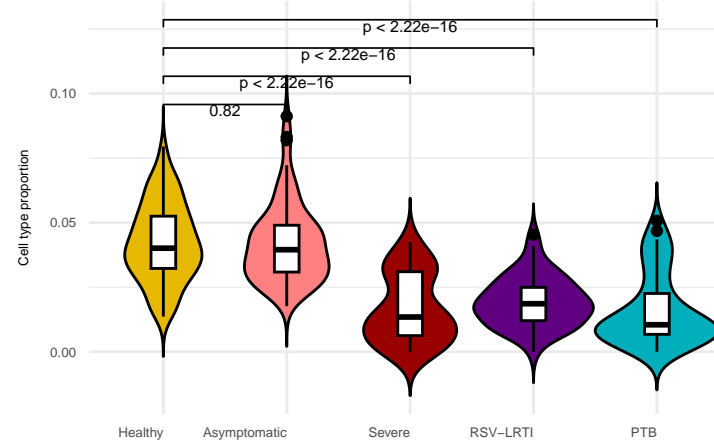
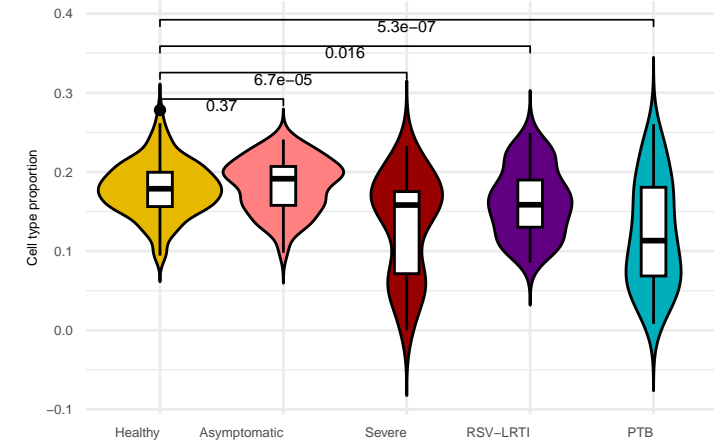
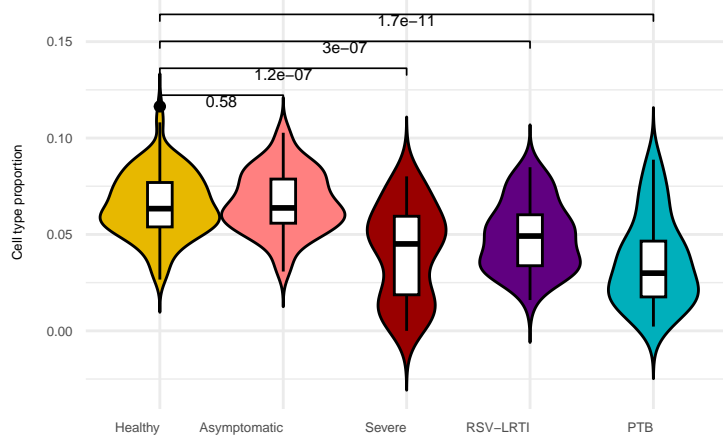
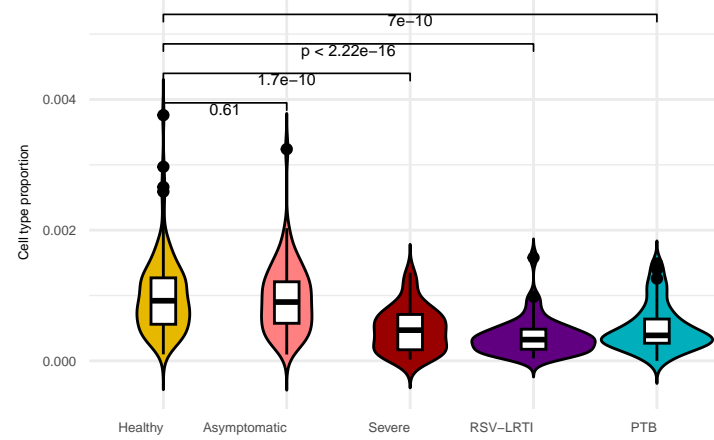
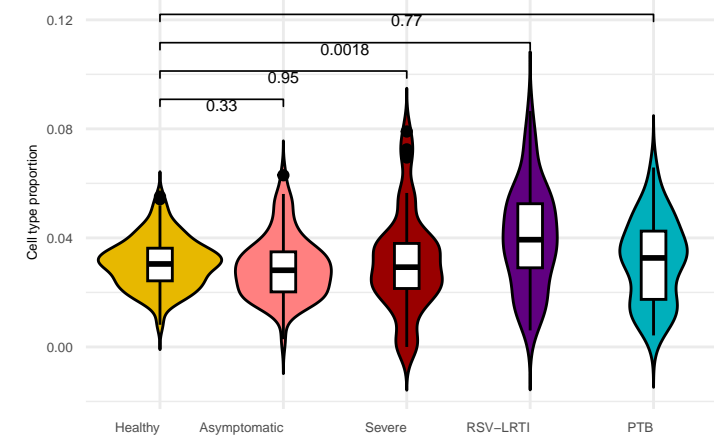
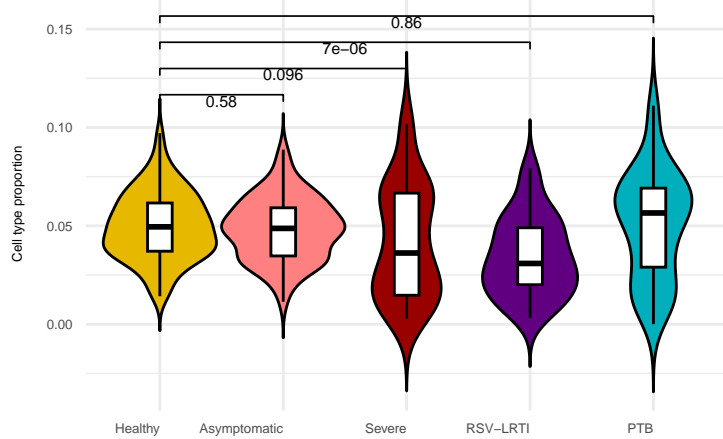
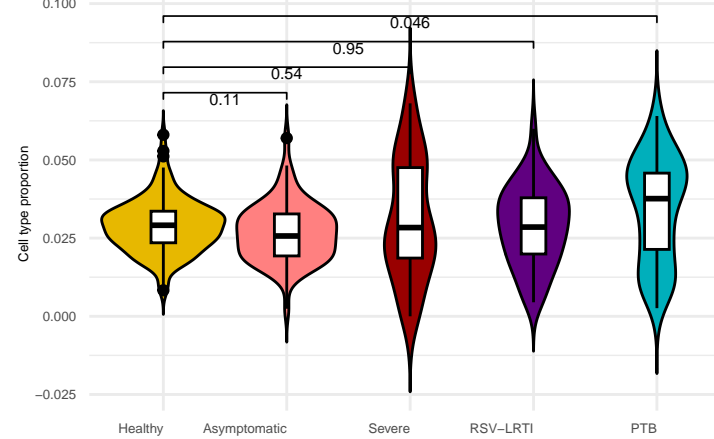
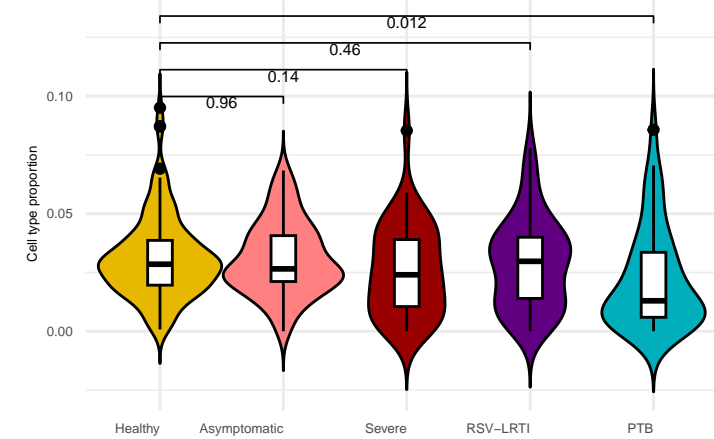


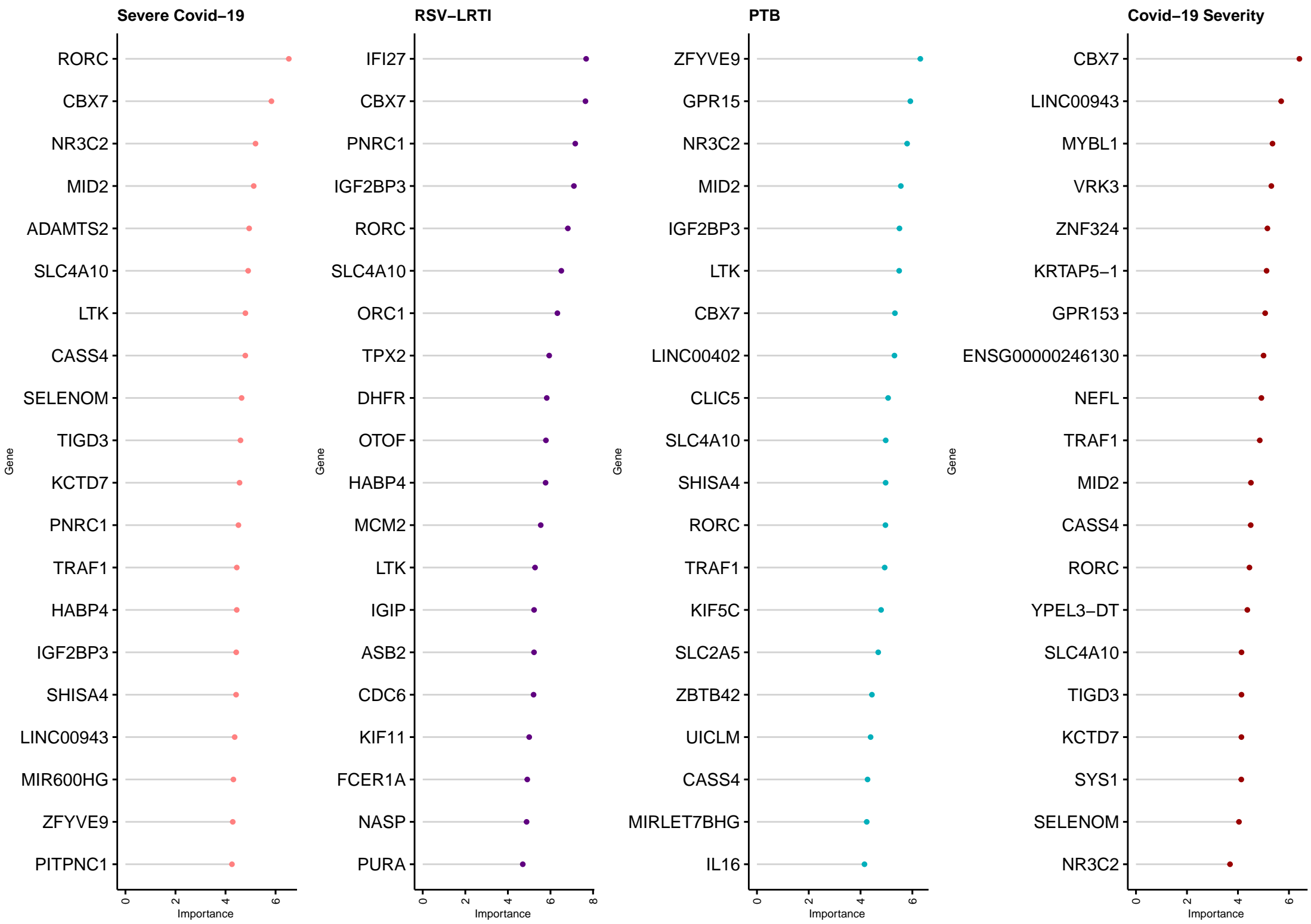
A



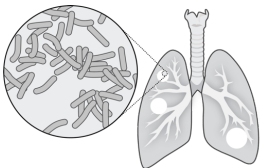
B



Macrophage**CD8+Ttm****T cell****Central memory CD8+*****Basophil****Non-classical monocyte****Granulocyte****Myeloid cell****Naive thymus derivedCD8+***



Respiratory infections



Healthy



Control n=127



Mild/Asymptomatic n=71



Severe n=41



n=47



SARS-CoV2

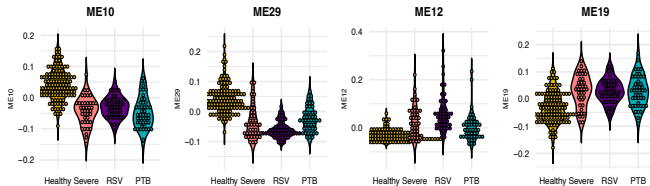


RSV-LRTI

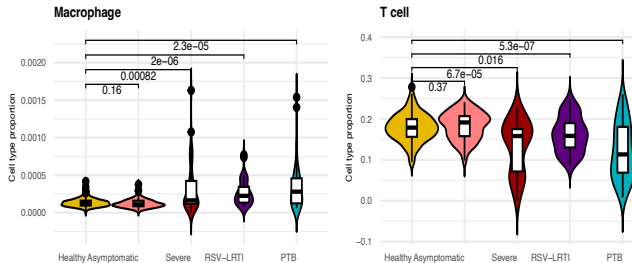


Pulmonary Tuberculosis n=47

Gene co-expression signatures



Lymphocyte dysregulation



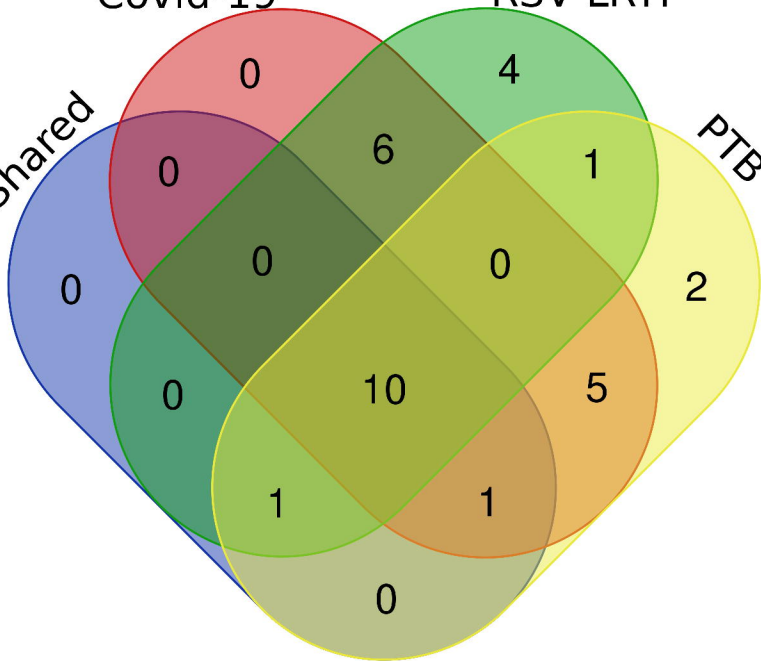


Covid-19

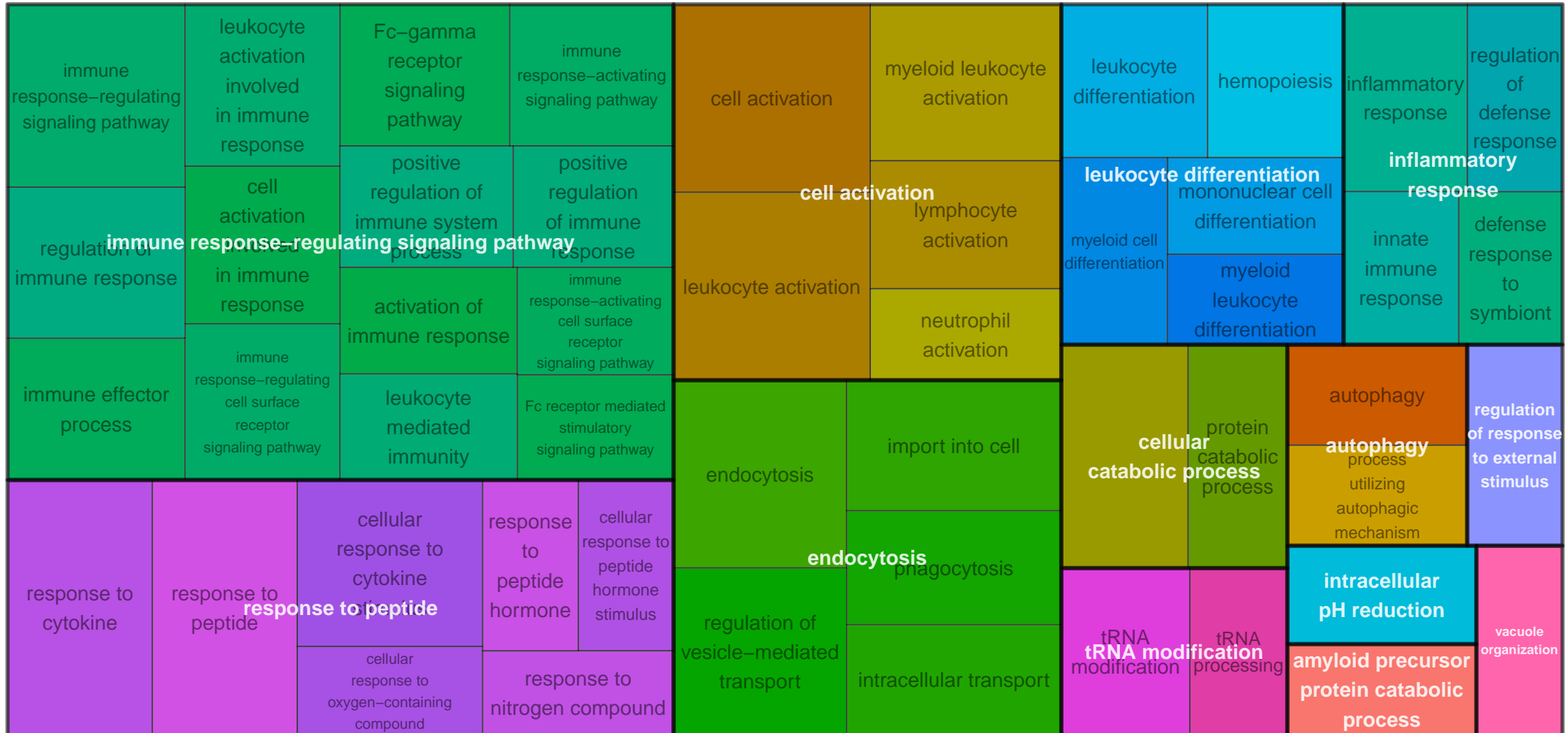
RSV-LRTI

PTB

Shared



ME1



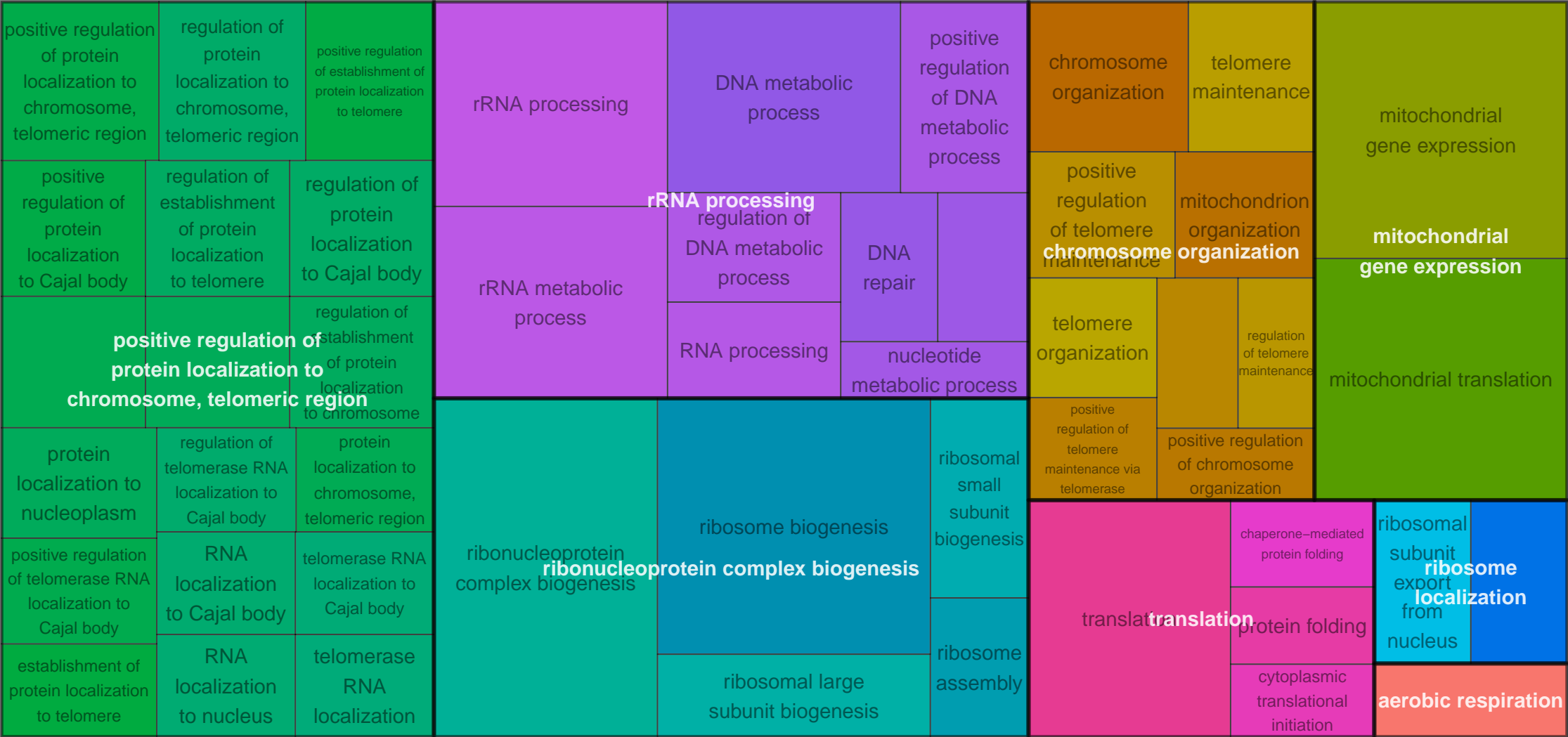
ME10

cytosolic transport

cytosolic transport
cytosolic transport, endosome to Golgi

endosomal transport

ME11

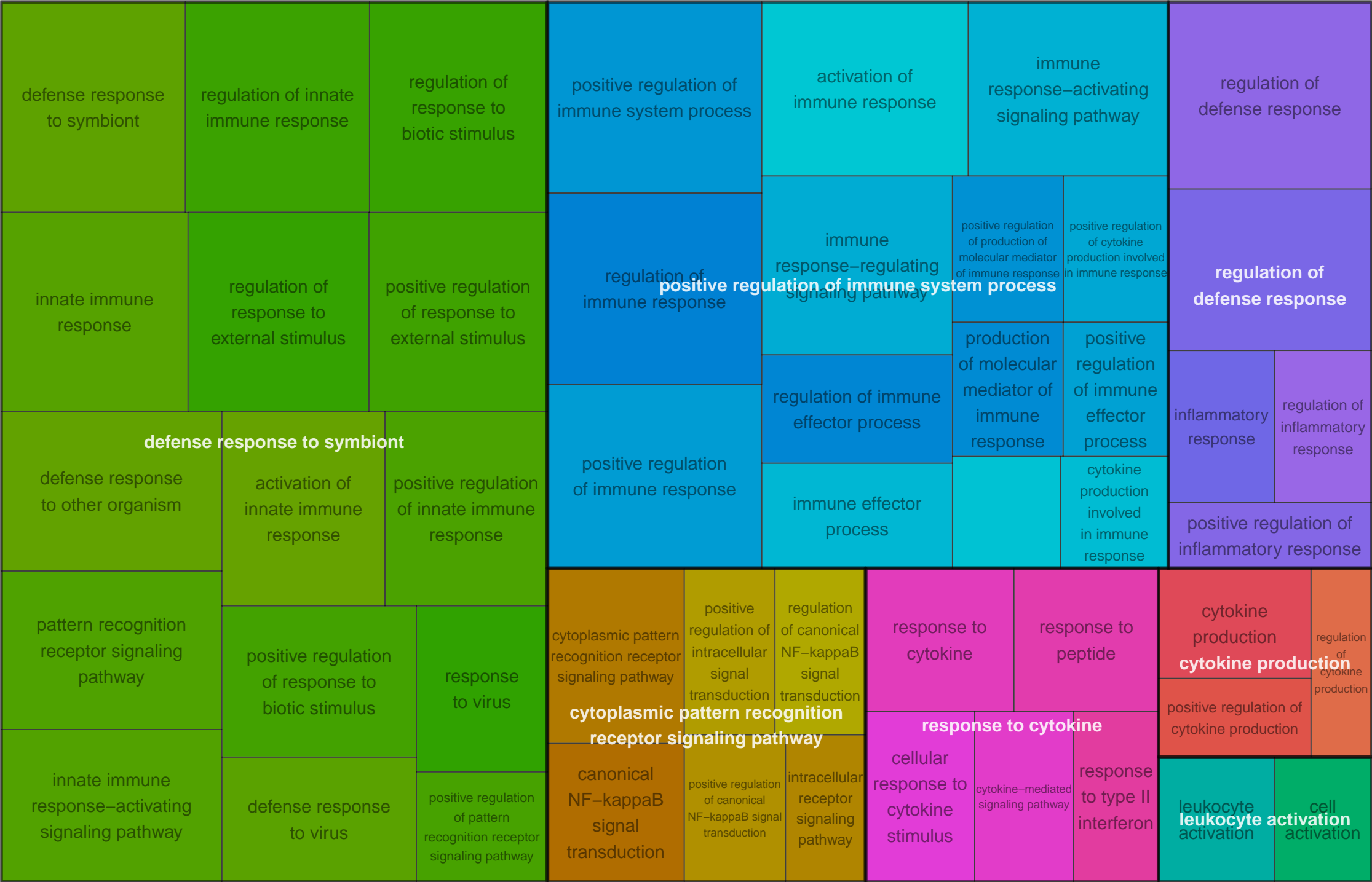


ME12

cell cycle process	regulation of cell cycle process	cell cycle phase transition	mitotic cell cycle phase transition	regulation of cell cycle phase transition	regulation of mitotic cell cycle phase transition	chromosome organization	mitotic nuclear division	protein–DNA complex assembly	nucleosome assembly		
	nuclear chromosome segregation	negative regulation of cell cycle process	cell cycle checkpoint signaling	regulation of chromosome segregation	negative regulation of cell cycle phase transition			protein–DNA complex organization	protein–DNA nucleosome organization		
mitotic cell cycle process	mitotic sister chromatid segregation	cell cycle process	positive regulation of cell cycle process	negative regulation of cell cycle	negative regulation of mitotic cell cycle phase transition	nuclear division	regulation of mitotic nuclear division			chromatin remodeling	chromatin organization
	mitotic cell cycle		sister chromatid segregation	chromosome separation	mitotic cell cycle checkpoint signaling			mitotic sister chromatid separation	regulation of sister chromatid segregation		
chromosome segregation		regulation of cell cycle	regulation of chromosome separation	regulation of mitotic sister chromatid separation	positive regulation of cell cycle	meiotic cell cycle	DNA replication	DNA replication process	DNA–templated DNA replication	DNA repair	DNA damage response

ME13

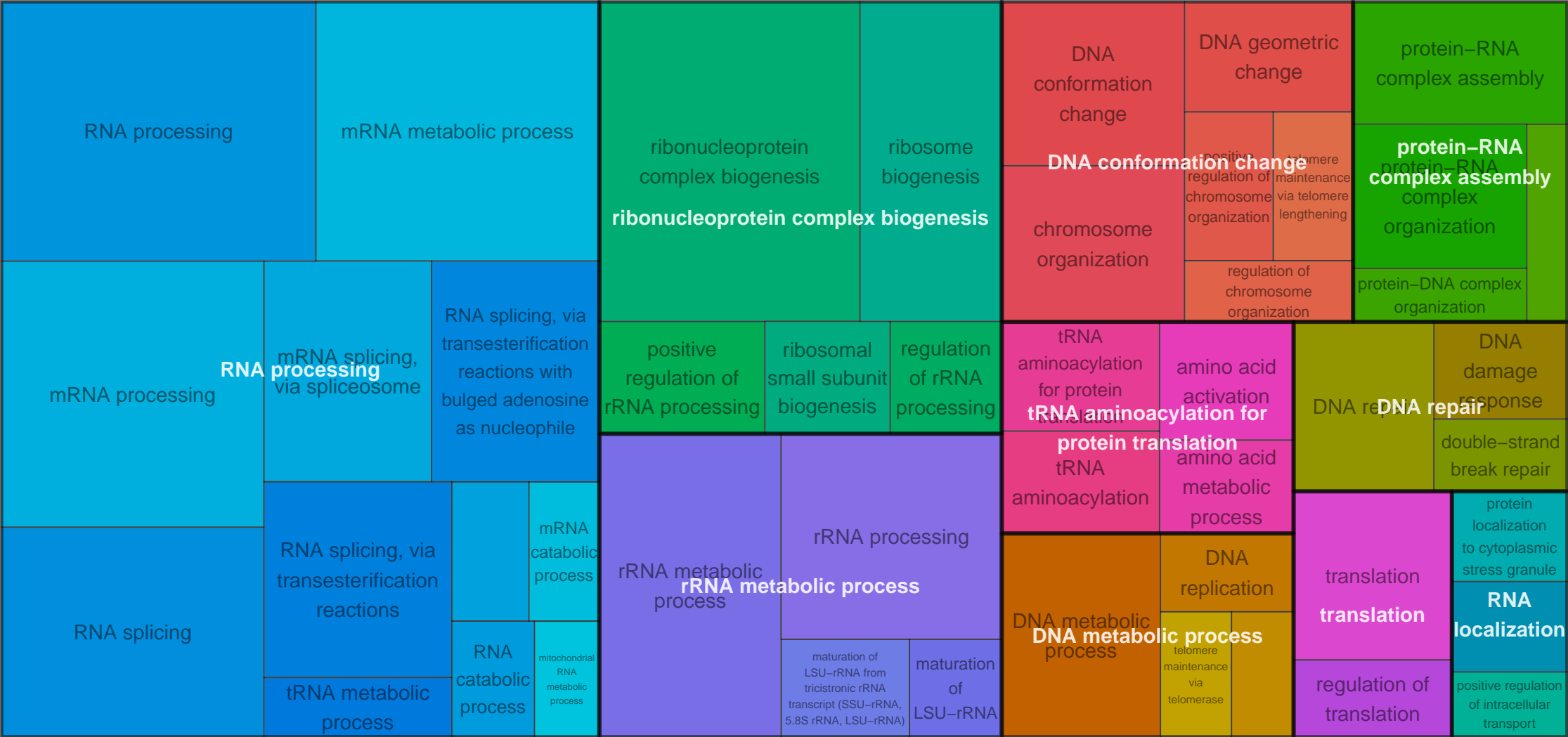
antigen processing and presentation of endogenous peptide antigen via MHC class I via ER pathway, TAP-dependent		antigen processing and presentation of endogenous peptide antigen via MHC class Ib		antigen processing and presentation of exogenous peptide antigen via MHC class I		antigen processing and presentation of peptide antigen via MHC class Ib		positive regulation of retrograde protein transport, ER to cytosol			retrograde protein transport, ER to cytosol		positive regulation of T cell mediated cytotoxicity		protection from natural killer cell mediated cytotoxicity		ERAD pathway		protein catabolic process				
		antigen processing and presentation of endogenous peptide antigen via MHC class I		antigen processing and presentation via MHC class Ib		antigen presentation of endogenous antigen		regulation of adaptive immune response		positive regulation of retrograde protein transport, ER to cytosol		exit from endoplasmic reticulum		positive regulation of leukocyte mediated cytotoxicity		regulation of T cell mediated cytotoxicity		positive regulation of cell killing		ERAD pathway			
antigen processing and presentation of endogenous peptide antigen via MHC class I via ER pathway, TAP-independent		antigen processing and presentation of endogenous peptide antigen		regulation of immune effector process		positive regulation of immune effector process		positive regulation of leukocyte mediated immunity		endoplasmic reticulum to cytosol transport			positive regulation of protein exit from endoplasmic reticulum			autophagy		process utilizing autophagic mechanism		positive regulation of interleukin-6 production		positive regulation of proteolysis	
detection of chemical stimulus involved in sensory perception of bitter taste		detection of chemical stimulus involved in sensory perception of taste		sensory bitter taste		sensory perception of taste		organelle fusion			vacuole organization		vesicle fusion		regulation of TORC1 signaling		endoplasmic reticulum calcium ion homeostasis		Golgi vesicle transport		regulation of response to biotic stimulus		



ME15

leukocyte activation		cell activation		lymphocyte activation		alpha-beta T cell activation		adaptive immune response		lymphocyte mediated immunity		regulation of immune response		positive regulation of natural killer cell mediated cytotoxicity		negative regulation of immune system process		defense response to other organism	
T cell activation		regulation of lymphocyte activation		alpha-beta T cell differentiation involved in immune response		lymphocyte activation involved in immune response		immune effector process		natural killer cell mediated cytotoxicity		positive regulation of natural killer cell mediated immunity		positive regulation of lymphocyte mediated immunity		positive regulation of immune system process		defense response to other organism	
		leukocyte activation involved in immune response		alpha-beta T cell differentiation		CD4-positive, alpha-beta T cell differentiation				T cell differentiation		regulation of lymphocyte mediated immunity		regulation of leukocyte mediated immunity		T cell mediated immunity			
regulation of leukocyte activation		CD4-positive, alpha-beta T cell activation		T cell differentiation involved in immune response		CD4-positive, alpha-beta T cell differentiation involved in immune response		leukocyte mediated immunity		natural killer cell mediated immunity		regulation of immune effector process		positive regulation of leukocyte mediated immunity		regulation of response to external stimulus		granzyme-mediated programmed cell death signaling pathway	
regulation of cell activation		cell activation involved in immune response		T cell activation involved in immune response		natural killer cell activation				regulation of natural killer cell activation		positive regulation of cell killing		positive regulation of cell killing		leukocyte mediated cytotoxicity		regulation of cell killing	
										positive regulation of cell killing		positive regulation of cell killing		leukocyte mediated cytotoxicity		regulation of cell killing		positive regulation of leukocyte mediated cytotoxicity	
																		cellular defense response	

ME16



ME18

regulation of viral process	regulation of viral life cycle	response to virus				regulation of response to biotic stimulus		regulation of innate immune response		positive regulation of innate immune response		defense response to symbiont		innate immune response		
negative regulation of viral process	negative regulation of viral genome replication					defense response to virus	positive regulation of response to biotic stimulus	activation of innate immune response		negative regulation of innate immune response						
							antiviral innate immune response	negative regulation of response to biotic stimulus		pattern recognition receptor signaling pathway						
regulation of viral genome replication	viral life cycle	response to type I interferon	response to interferon-α	response to interferon-β	regulation of type I interferon-mediated signaling pathway			response to peptide		regulation of response to external stimulus		activation of immune response		positive regulation of response to external stimulus		symbiont entry into host cell
					cytoplasmic pattern recognition receptor signaling pathway		innate immune response-activating signaling pathway		regulation of immune response		positive regulation of immune response		immune response-activating signaling pathway		symbiont entry into host cell	
viral process	viral genome replication				cellular response to type I interferon	type I interferon-mediated signaling pathway	response to cytokine	negative regulation of type I interferon-mediated signaling pathway		regulation of response to cytokine stimulus		regulation of type I interferon production		regulation of type I interferon production		positive regulation of interferon-β production

ME2

homophilic cell adhesion via plasma membrane

adhesion molecules

cell-cell adhesion

plasma-membrane
adhesion molecules

import across
plasma
membrane

import across
plasma
membrane

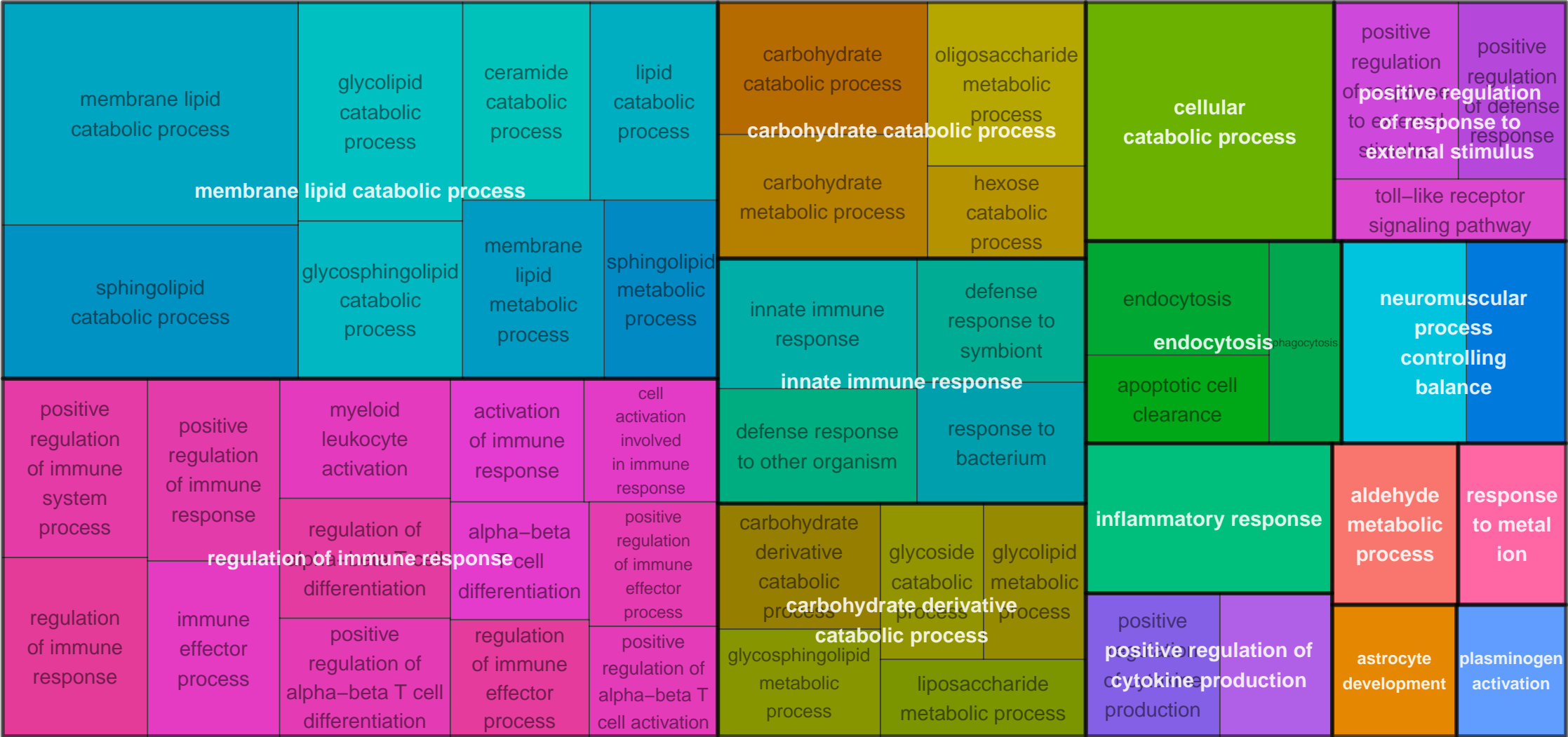
inorganic ion
import across
plasma
membrane

monoatomic
ion
transmembrane
transport

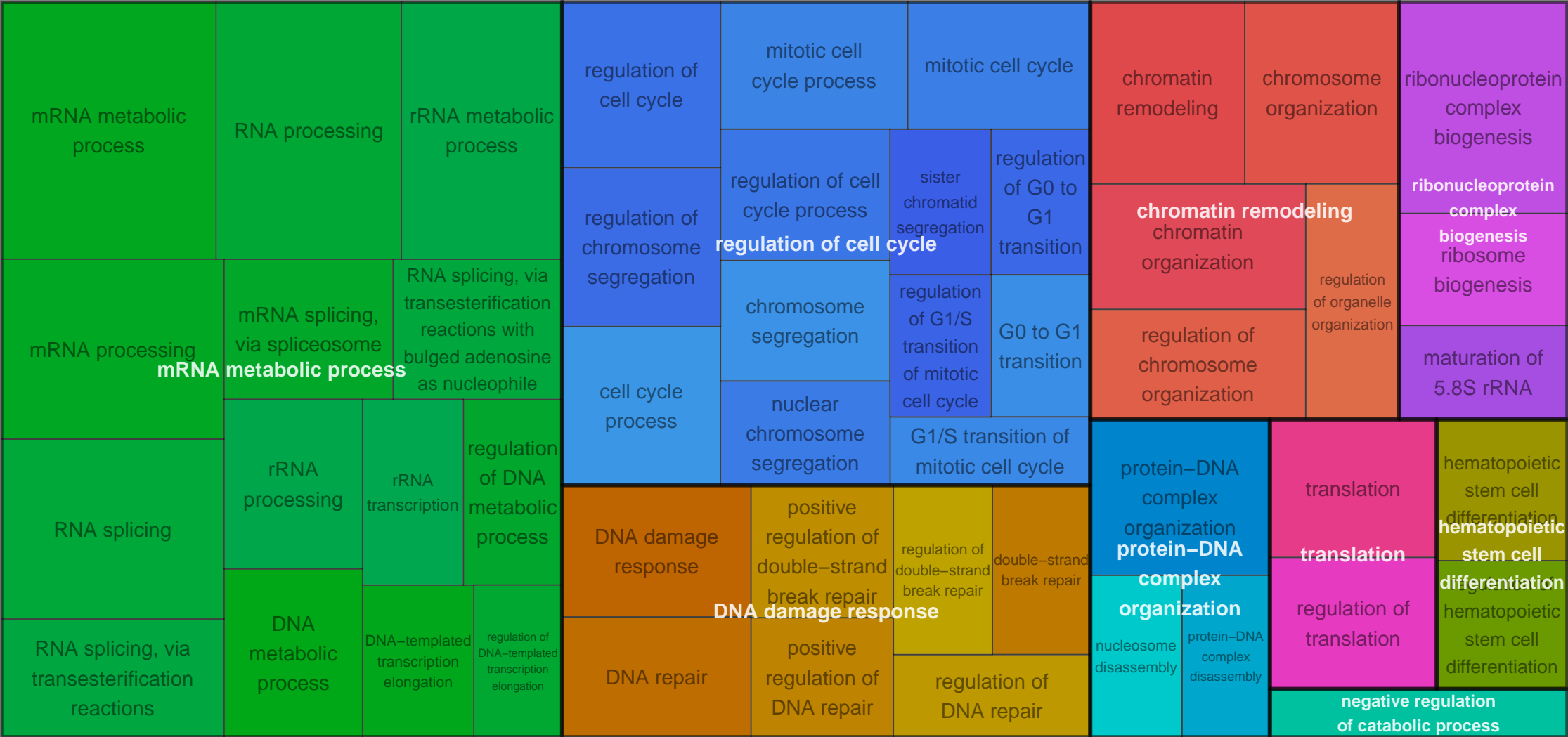
cell junction
organization

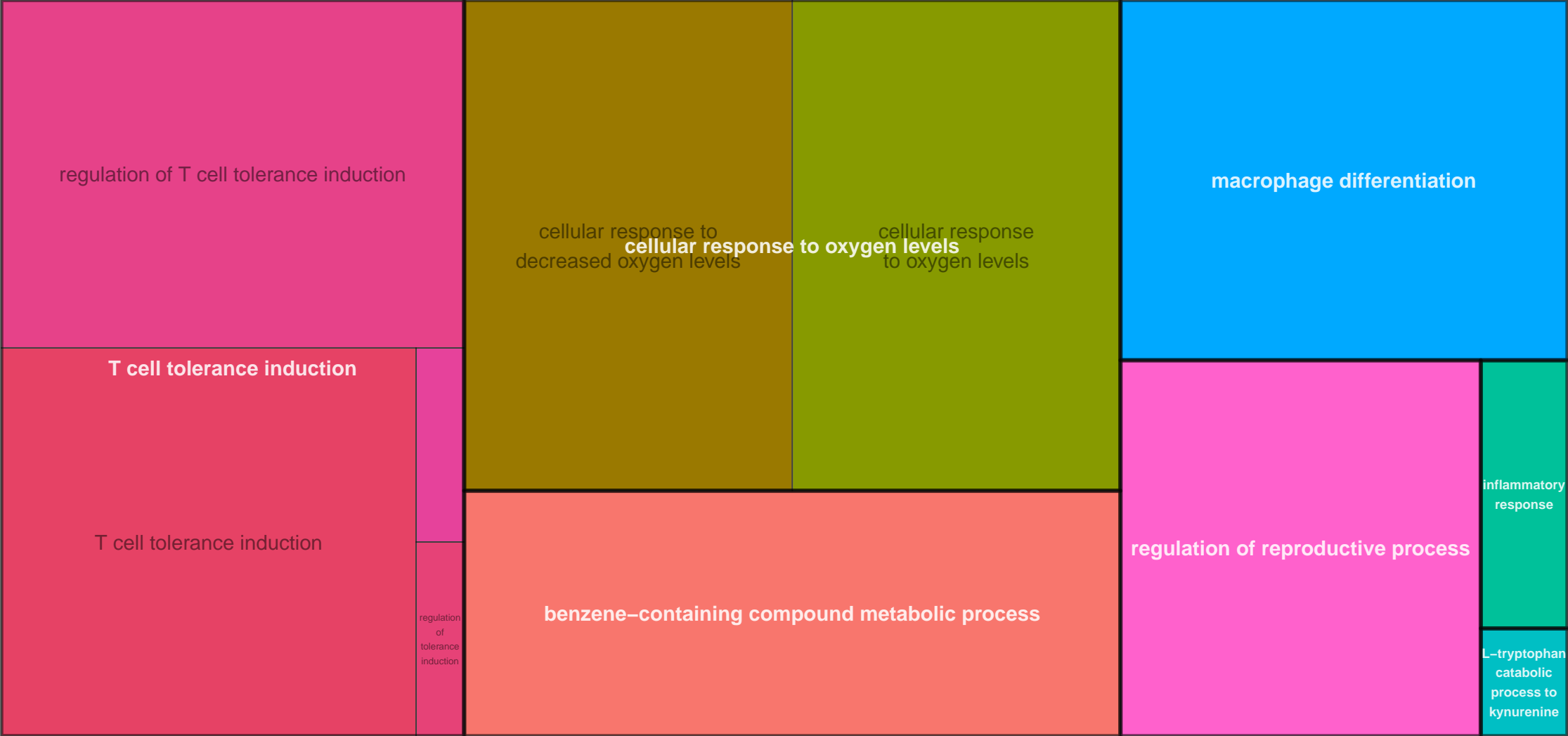
detection of
stimulus

ME20

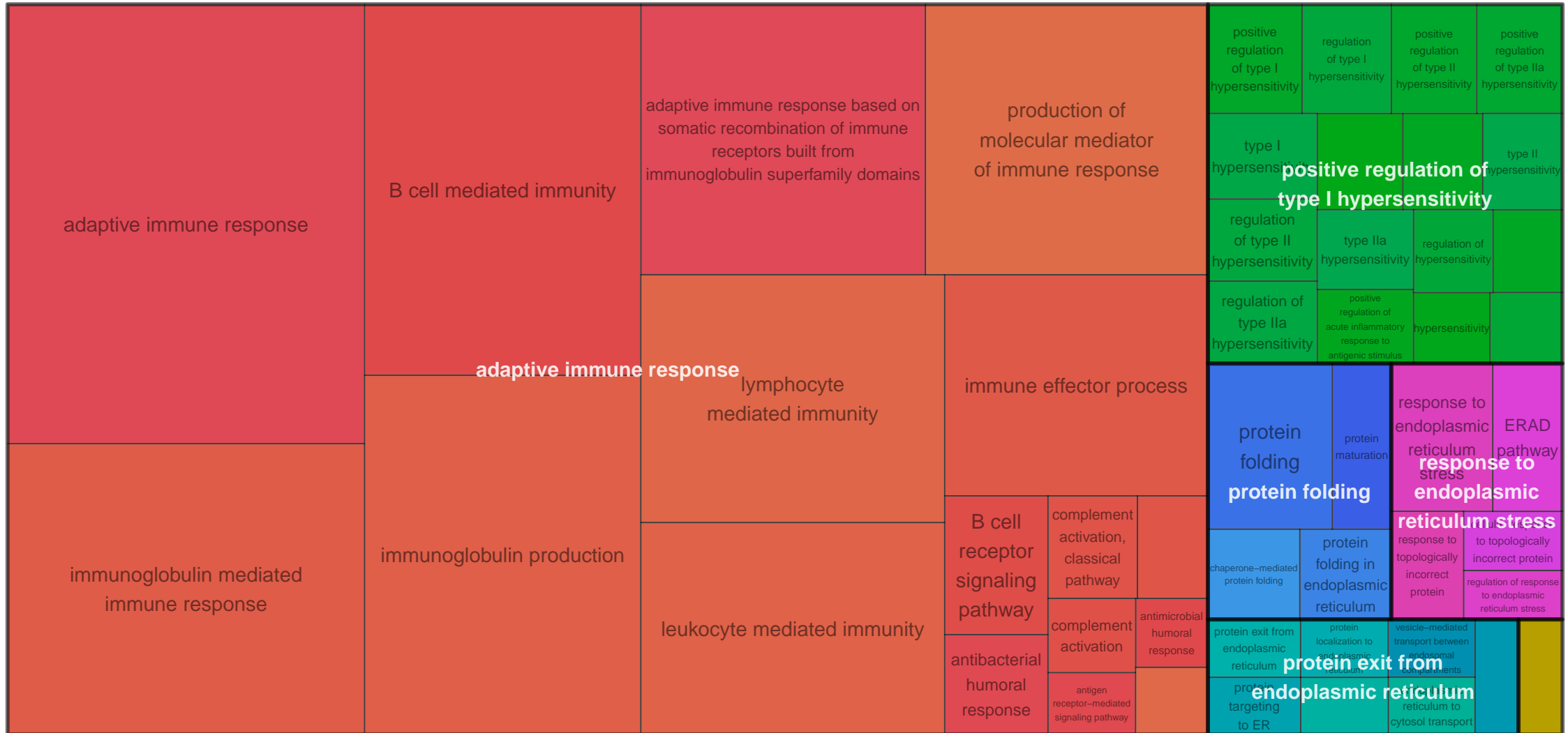


ME21

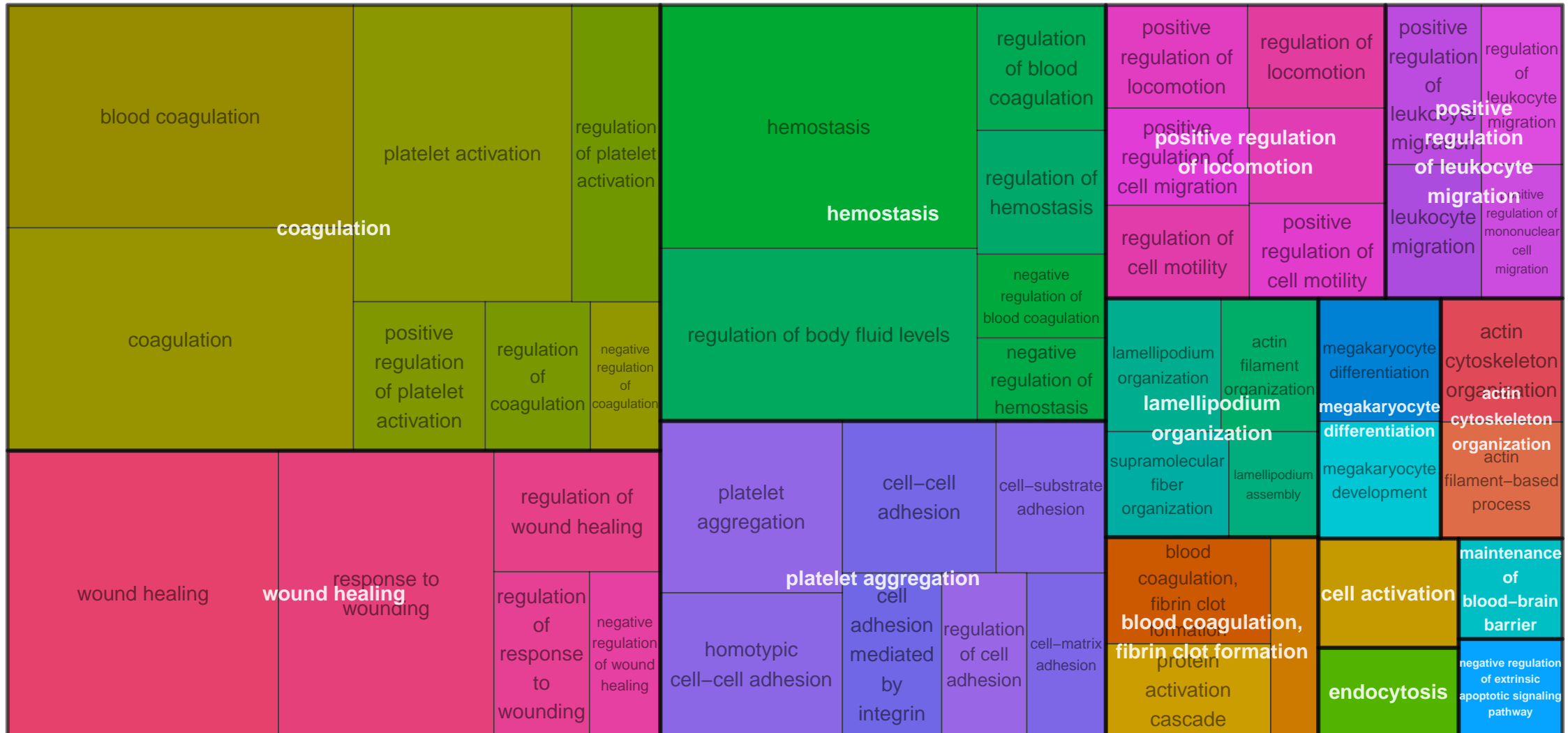




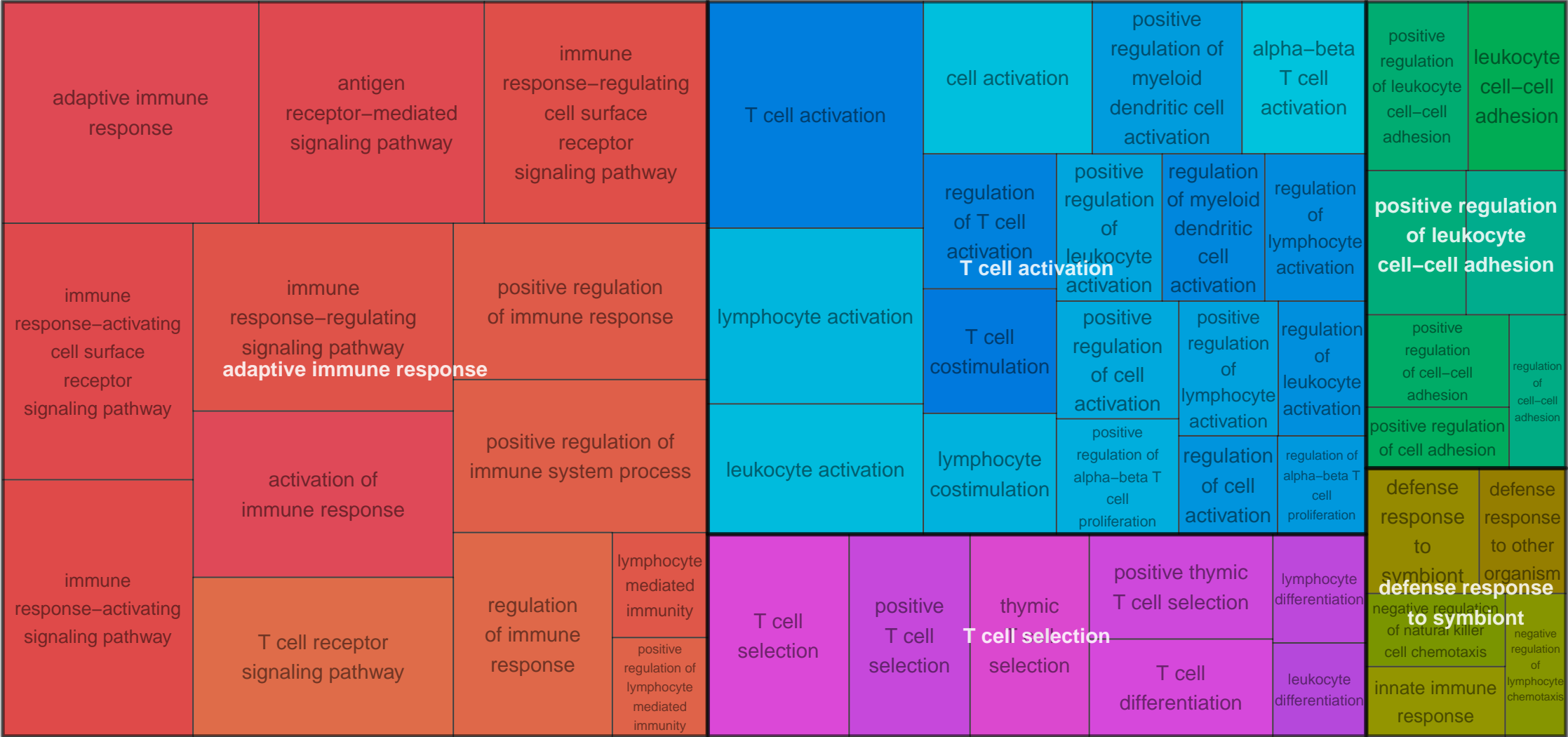
ME24



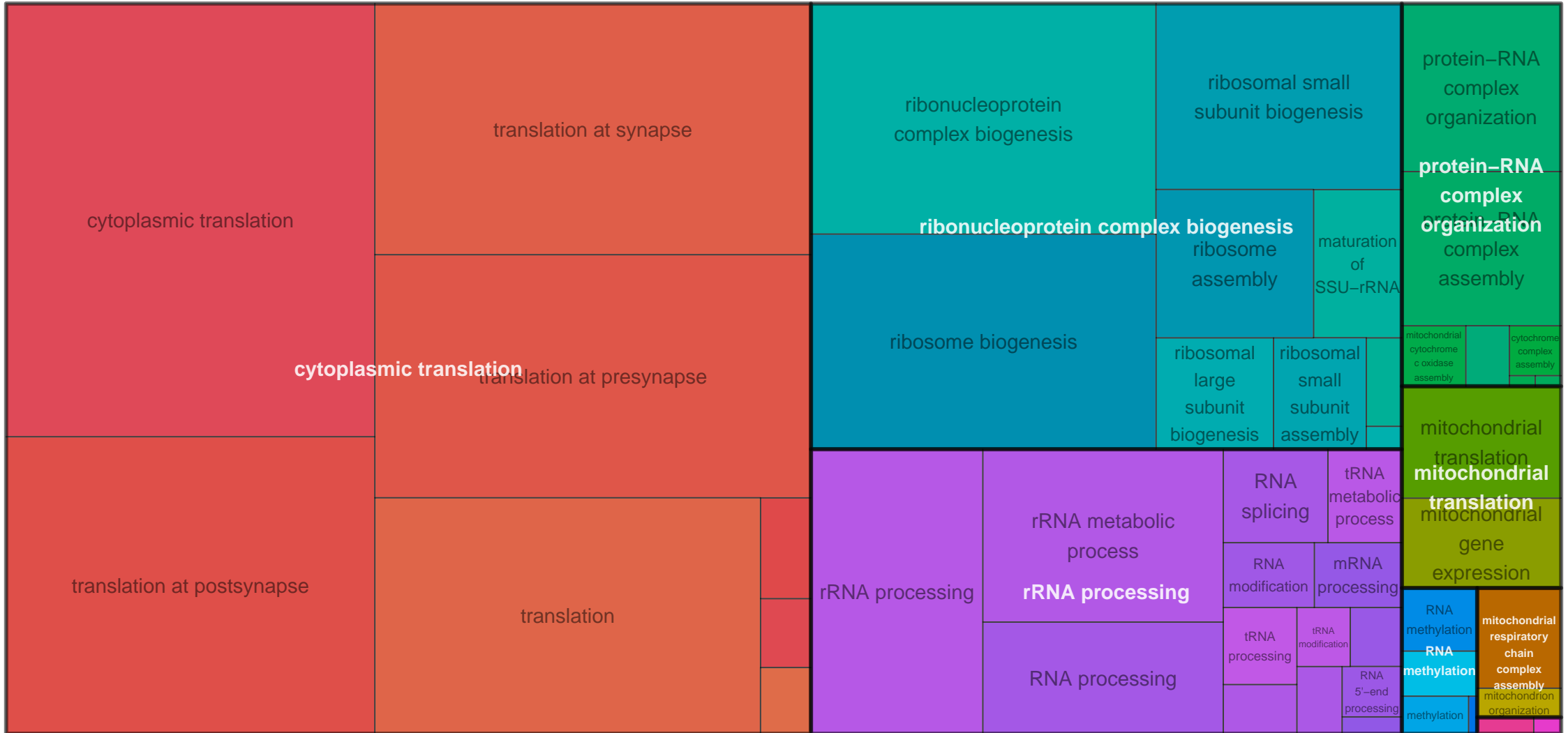
ME25







ME3



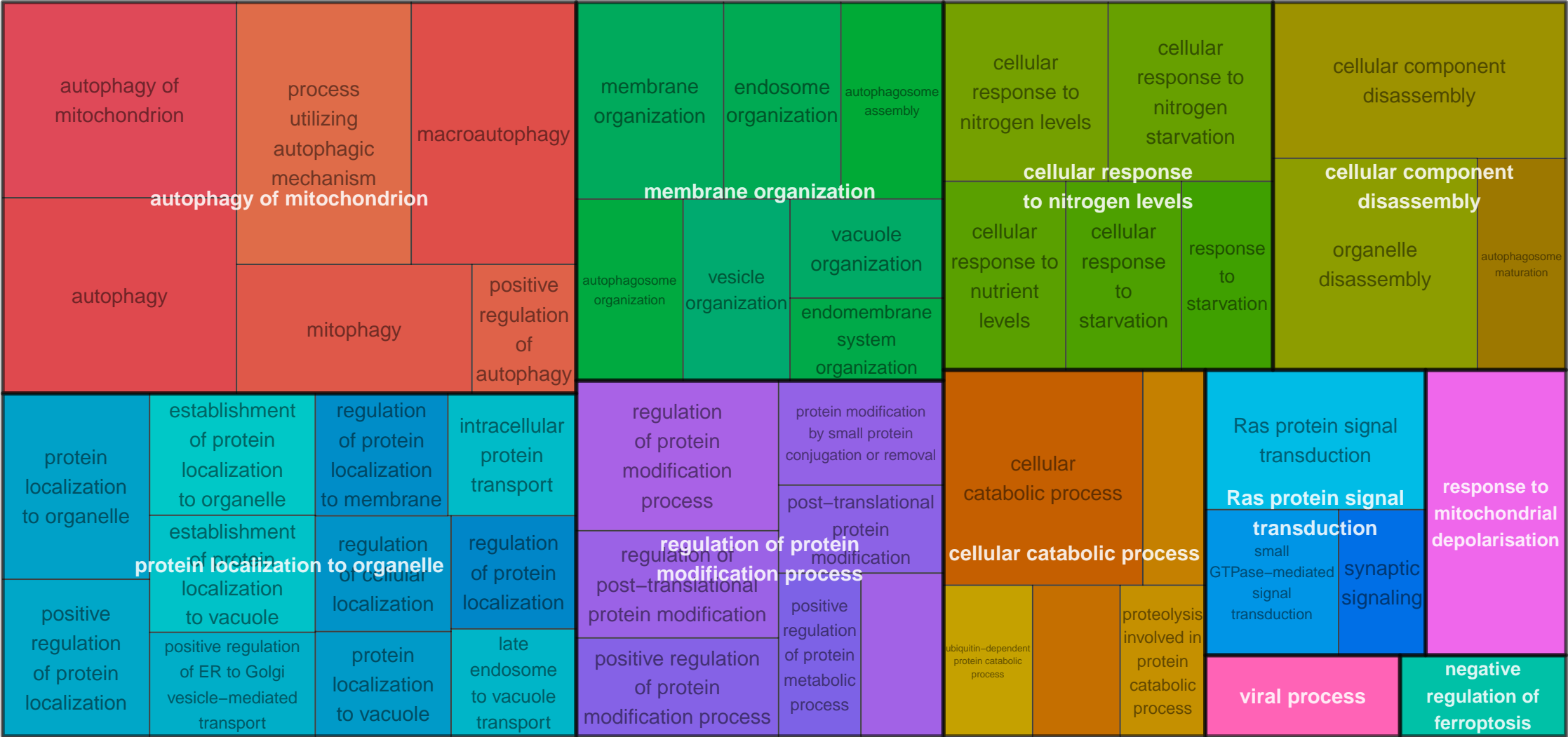
ME32

nuclear transport

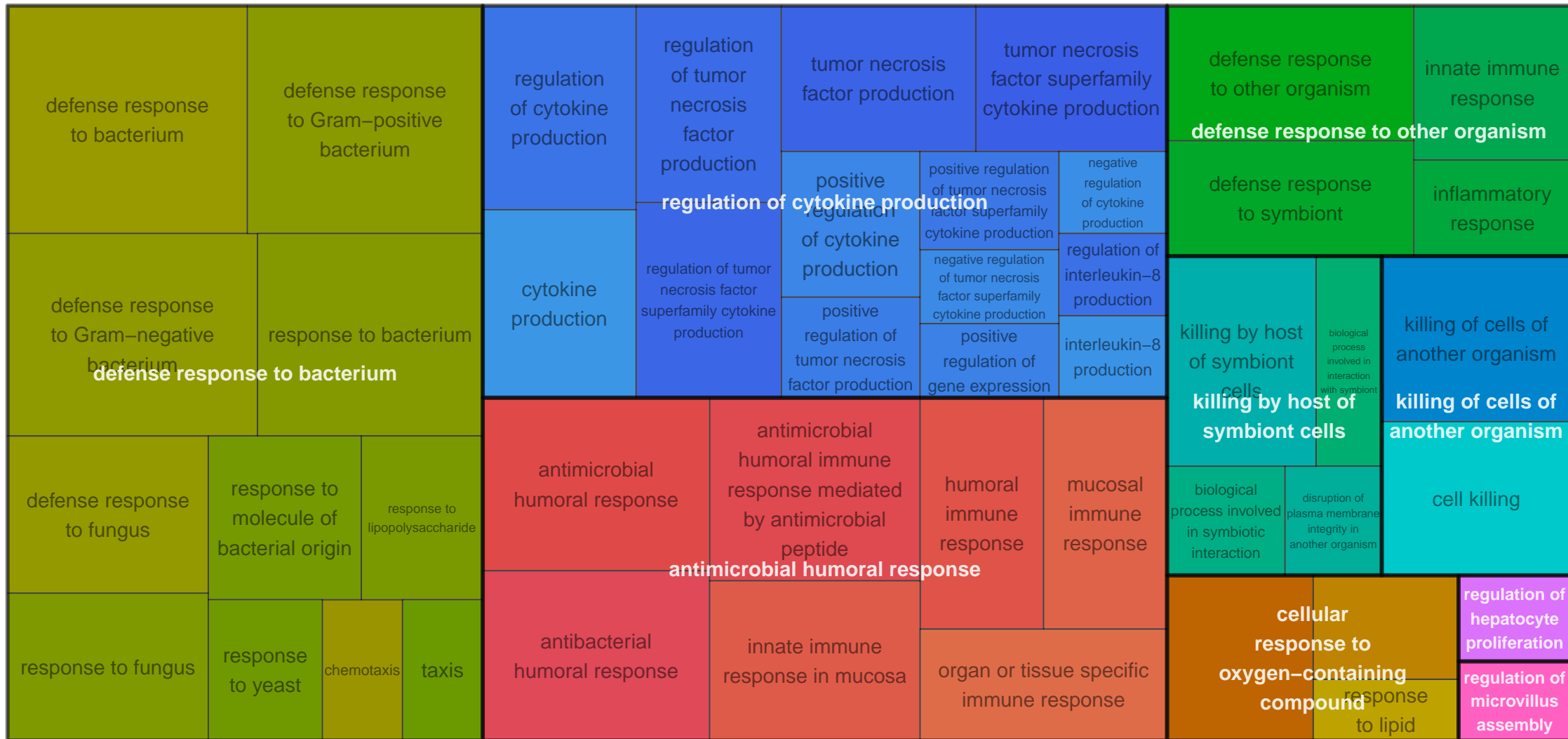
nucleocytoplasmic transport

nucleocytoplasmic transport

ME33



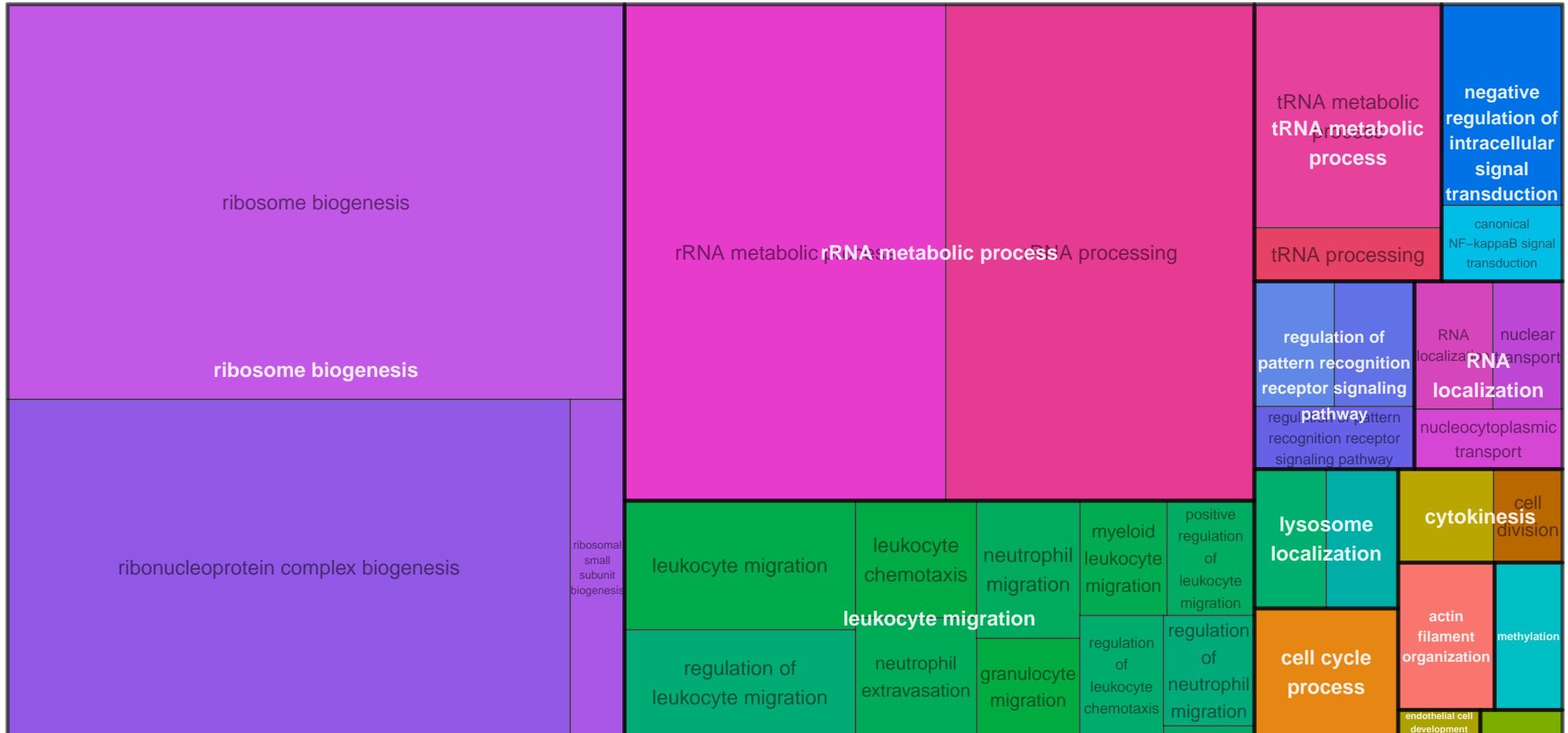
ME34

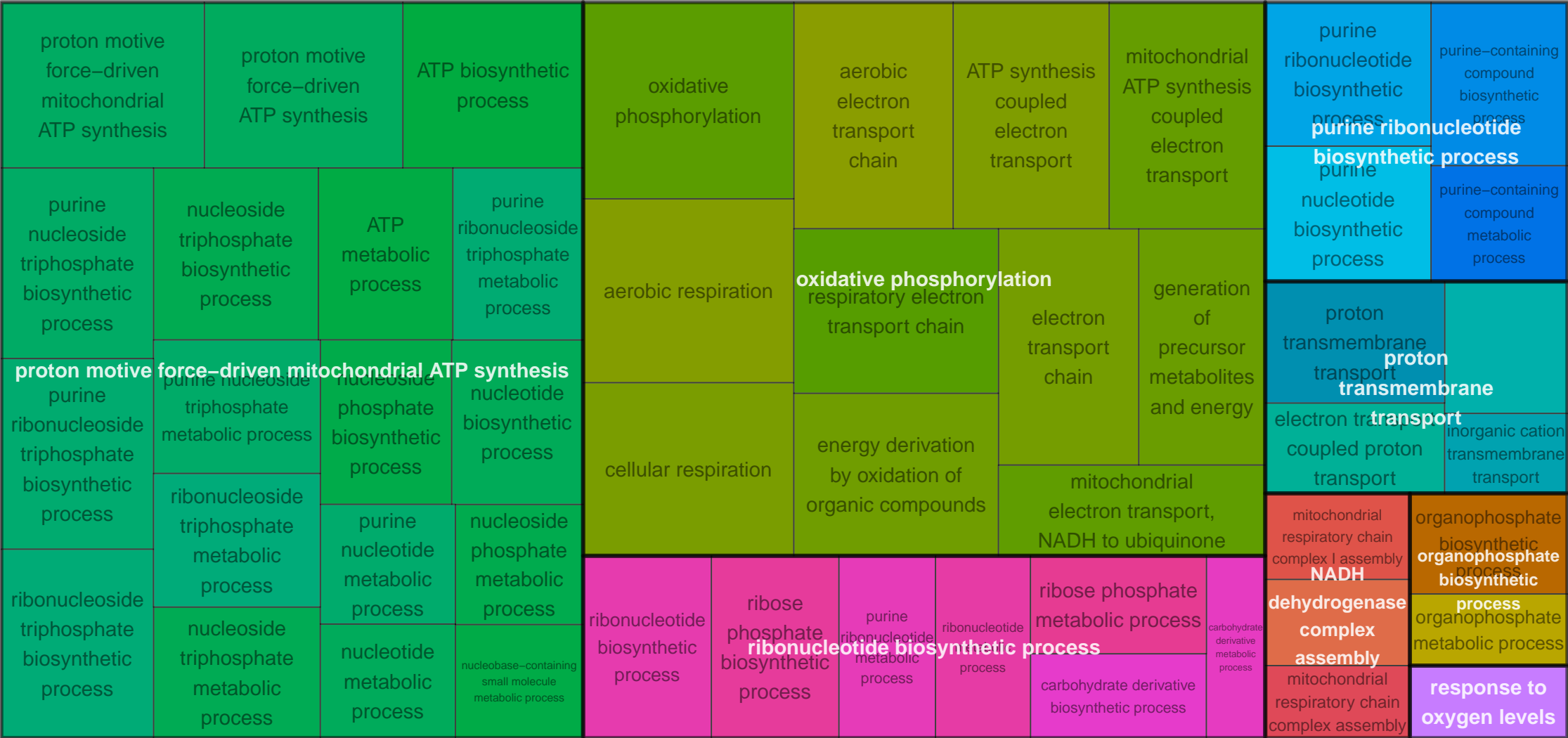


ME38

positive regulation of carbohydrate metabolic process	regulation of carbohydrate metabolic process	regulation of carbohydrate biosynthetic process	glucan biosynthetic process		glycogen biosynthetic process	organic acid metabolic process	oxoacid metabolic process	cellular response to nitrogen compound	response to nitrogen compound	regulation of cell migration	regulation of cell motility
		positive regulation of carbohydrate metabolic process									
positive regulation of glycogen biosynthetic process	positive regulation of glycogen metabolic process	regulation of glucan biosynthetic process		glycogen metabolic process		carboxylic acid metabolic process	positive regulation of small molecule metabolic process	cellular response to oxygen-containing compound		regulation of locomotion	
		regulation of glycogen biosynthetic process		regulation of polysaccharide biosynthetic process							
cellular response to corticosteroid stimulus	cellular response to hormone stimulus	response to hormone		response to growth factor		intrinsic apoptotic signaling pathway in response to DNA damage	positive regulation of MAPK cascade	positive regulation of protein phosphorylation		regulation of phosphorus metabolic process	mononuclear cell proliferation
cellular response to glucocorticoid stimulus	cellular response to steroid hormone stimulus	response to corticosteroid	response to glucocorticoid	response to steroid hormone	intrinsic apoptotic signaling pathway in response to DNA damage	positive regulation of MAPK cascade	epithelial cell migration	tissue migration	positive regulation of D-glucose import	regulation of generation of precursor metabolites and energy	response to abiotic stimulus

ME4





ME7

detection of chemical
stimulus involved in
sensory perception of smell

**detection of chemical stimulus involved
in sensory perception of smell**

sensory perception of smell

sensory perception of chemical stimulus

detection of chemical stimulus
involved in sensory perception

detection of chemical stimulus

detection of stimulus involved
in sensory perception

detection of chemical stimulus

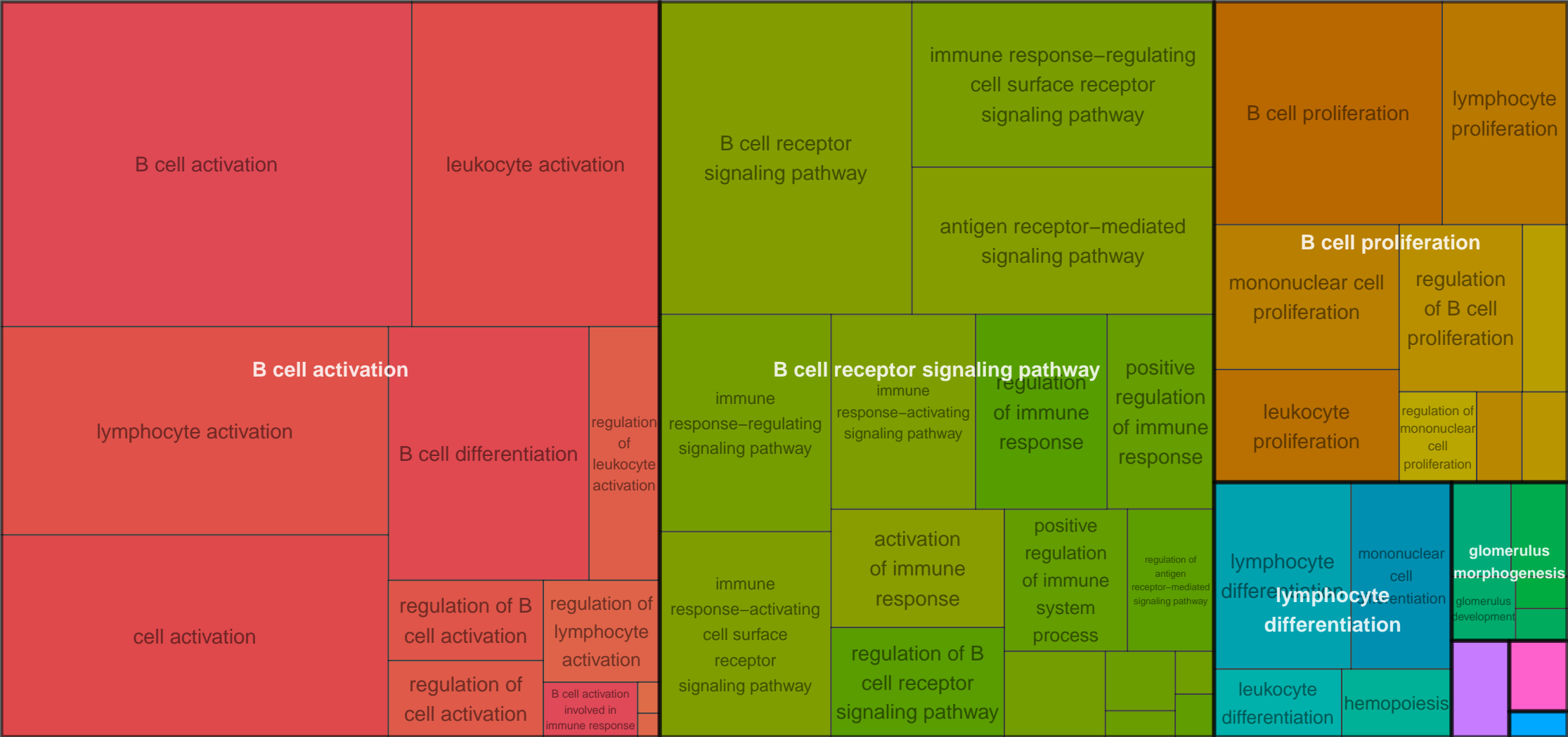
detection of stimulus

positive regulation of
telomere maintenance in
response to DNA damage

**positive regulation of
telomere maintenance in
response to DNA damage**
strand elongation

regulation of telomere
maintenance in
response to DNA damage

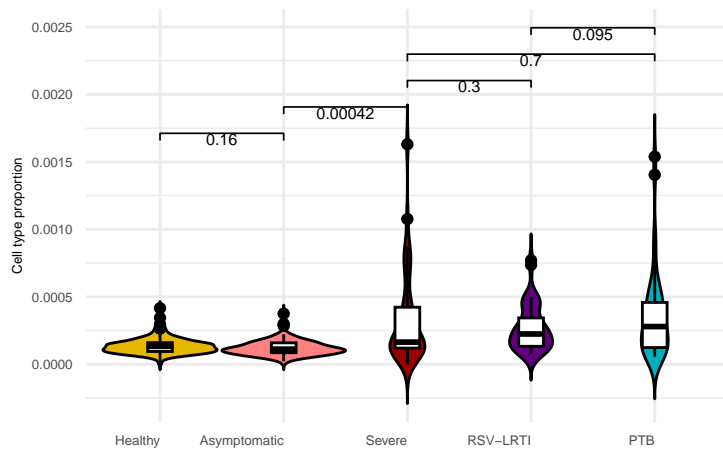
ME8



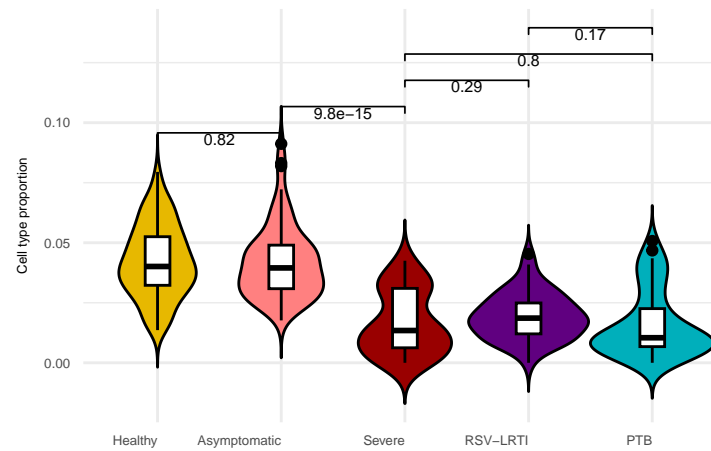
ME9



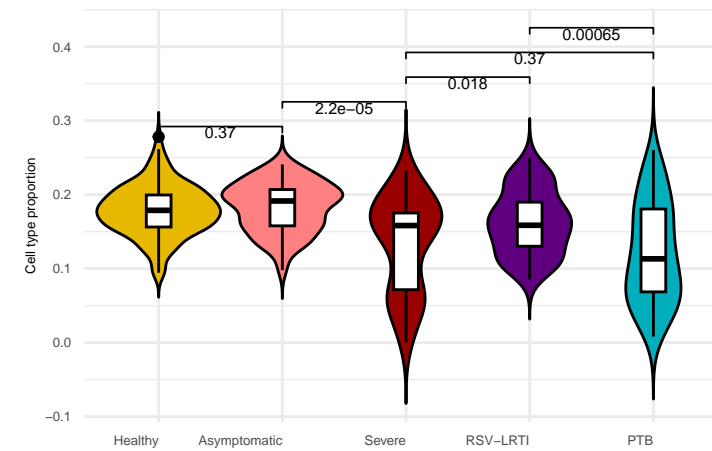
Macrophage



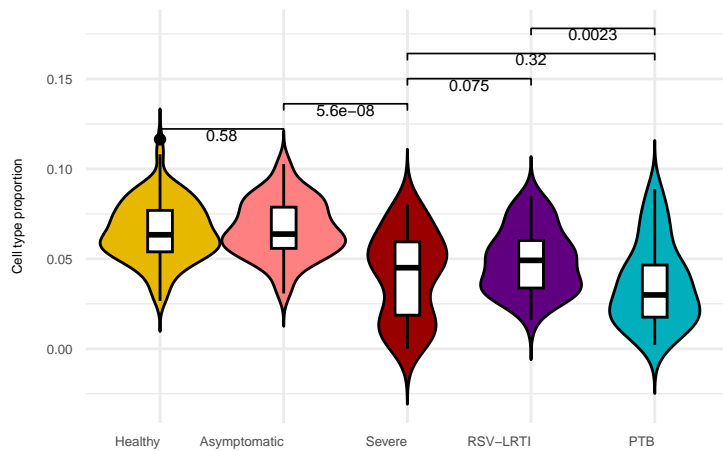
CD8+Ttm



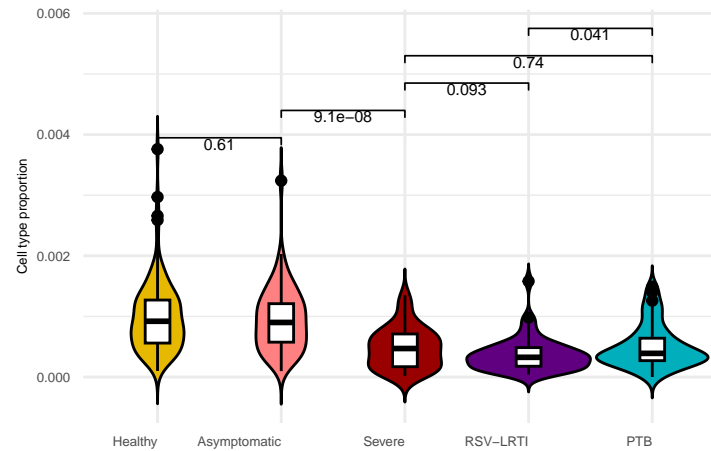
T cell



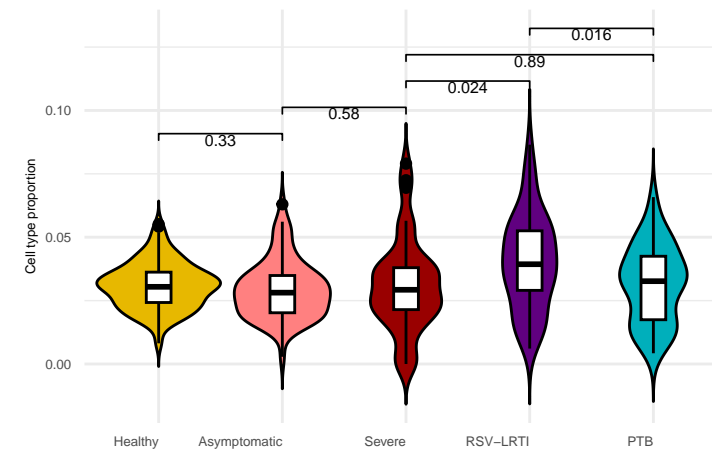
Central memory CD8+



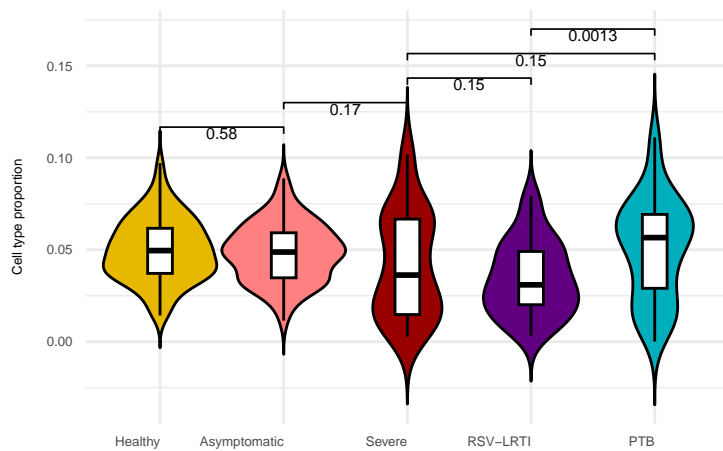
Basophil



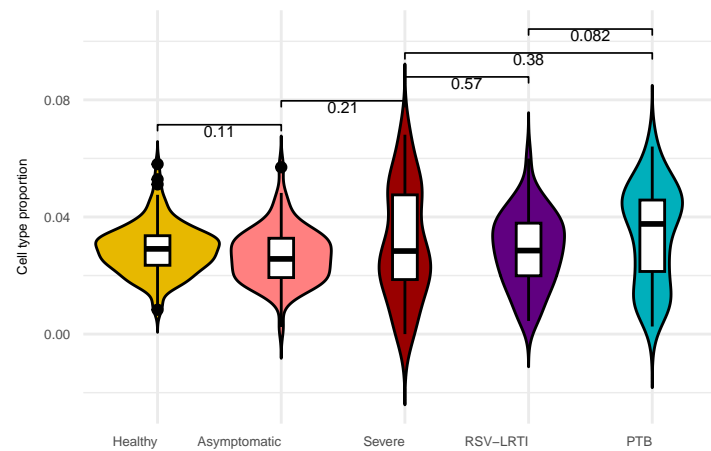
Non-classical monocyte



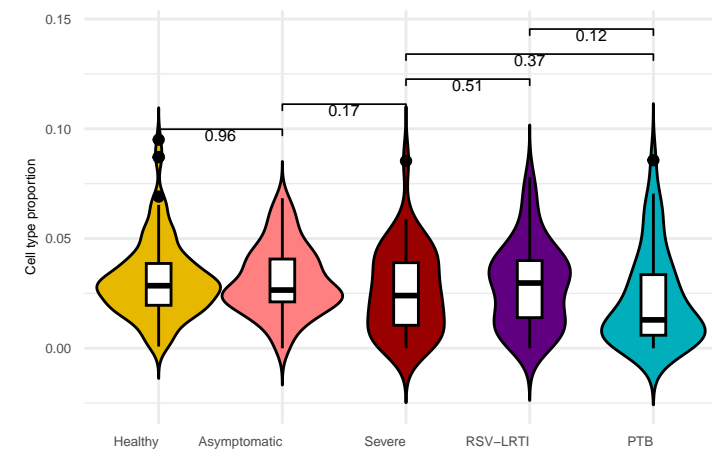
Granulocyte



Myeloid cell



Naive thymus derivedCD8+





Card 4 (100%)

Card 2 (100%)

Card 3 (100%)

Card 5 (100%)

