

Differential expression analysis of COVID vaccine reactogenicity Code ▾

Introduction

The COVIRS dataset allows a complex, deep analysis of vaccine response. Ryan et al. (2022) (<https://www.medrxiv.org/content/10.1101/2022.09.22.22280180v1>) found a few variables associated with individual symptoms (e.g., lower TFNa and chills after second dose of Pfizer), but only tested presence/absence of individual symptoms for associations.

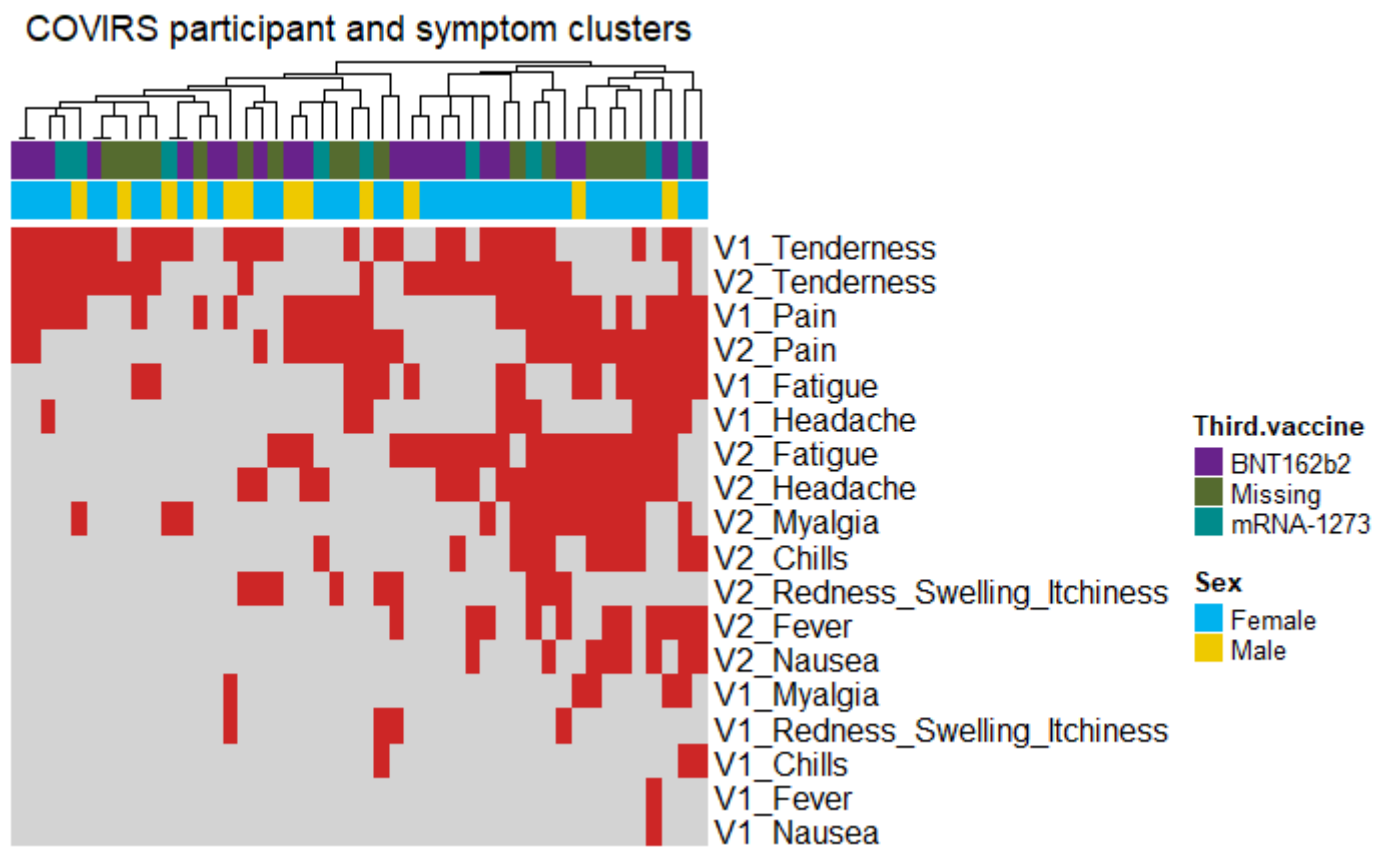
Here, I sought to take this line of thinking further by finding groups of participants based on all symptoms, comparing gene expression between the two groups after the second dose of Pfizer (V2), and seeing if any differences can be detected between the same groups at V0 (i.e., before vaccination).

Briefly, two groups were identified - symptomatic and asymptomatic. At V2 (28 days after the second vaccine dose), CNOT7 is significantly underexpressed in the symptomatic group. GSEA found cell signature differences using blood transcriptional modules from Li et al. (2014) (<https://pubmed.ncbi.nlm.nih.gov/24336226/>), identifying NK and B cells as more active in the symptomatic group, partly confirmed by a statistically significant lower B cell count from flow cytometry. At V0 (prior to the first vaccine dose), cell composition differences were unclear, but a few individual genes were significantly differentially expressed, including RNU1-4, an snRNA with unclear function that was overexpressed in the asymptomatic group.

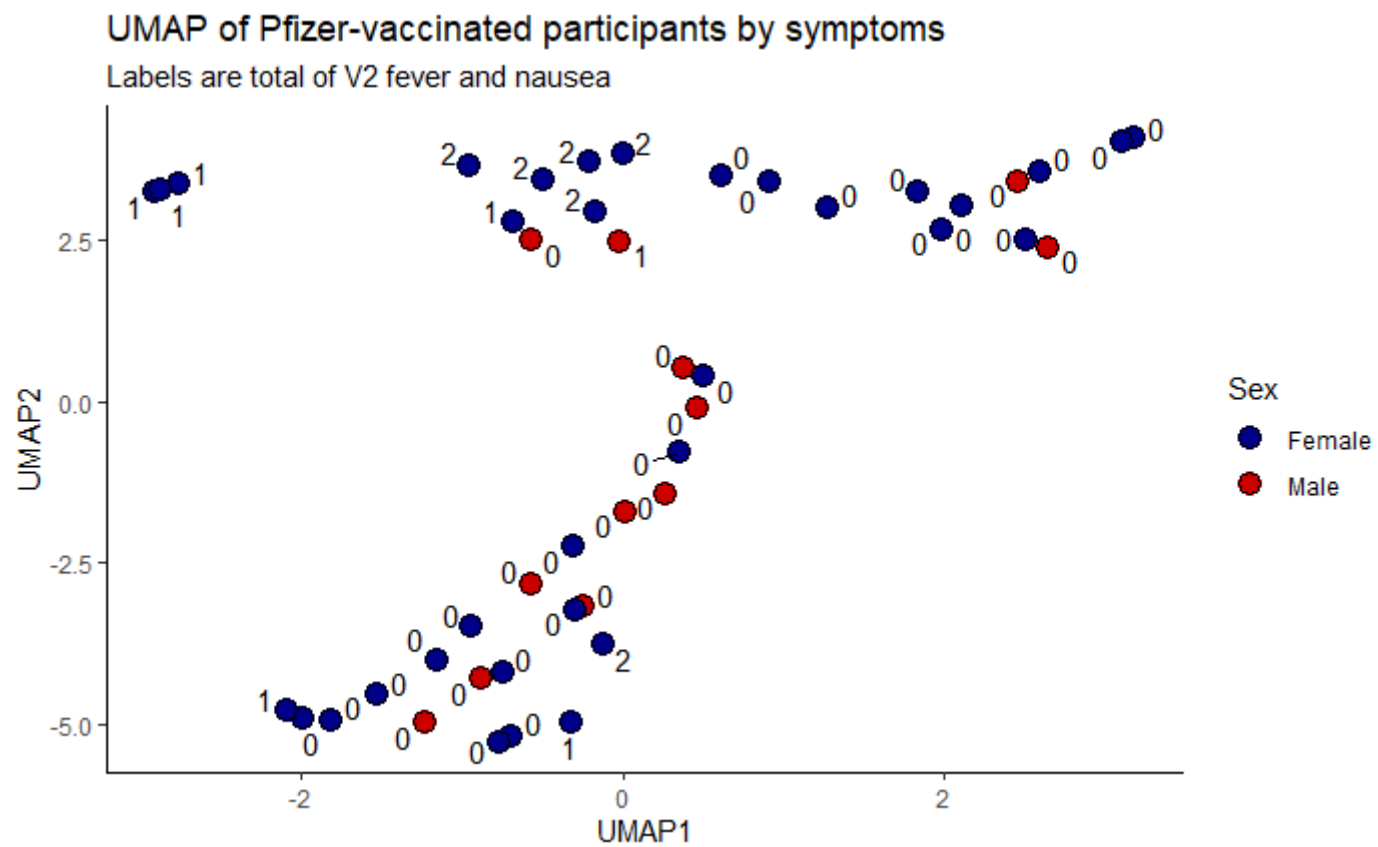
Defining patient groups based on symptoms

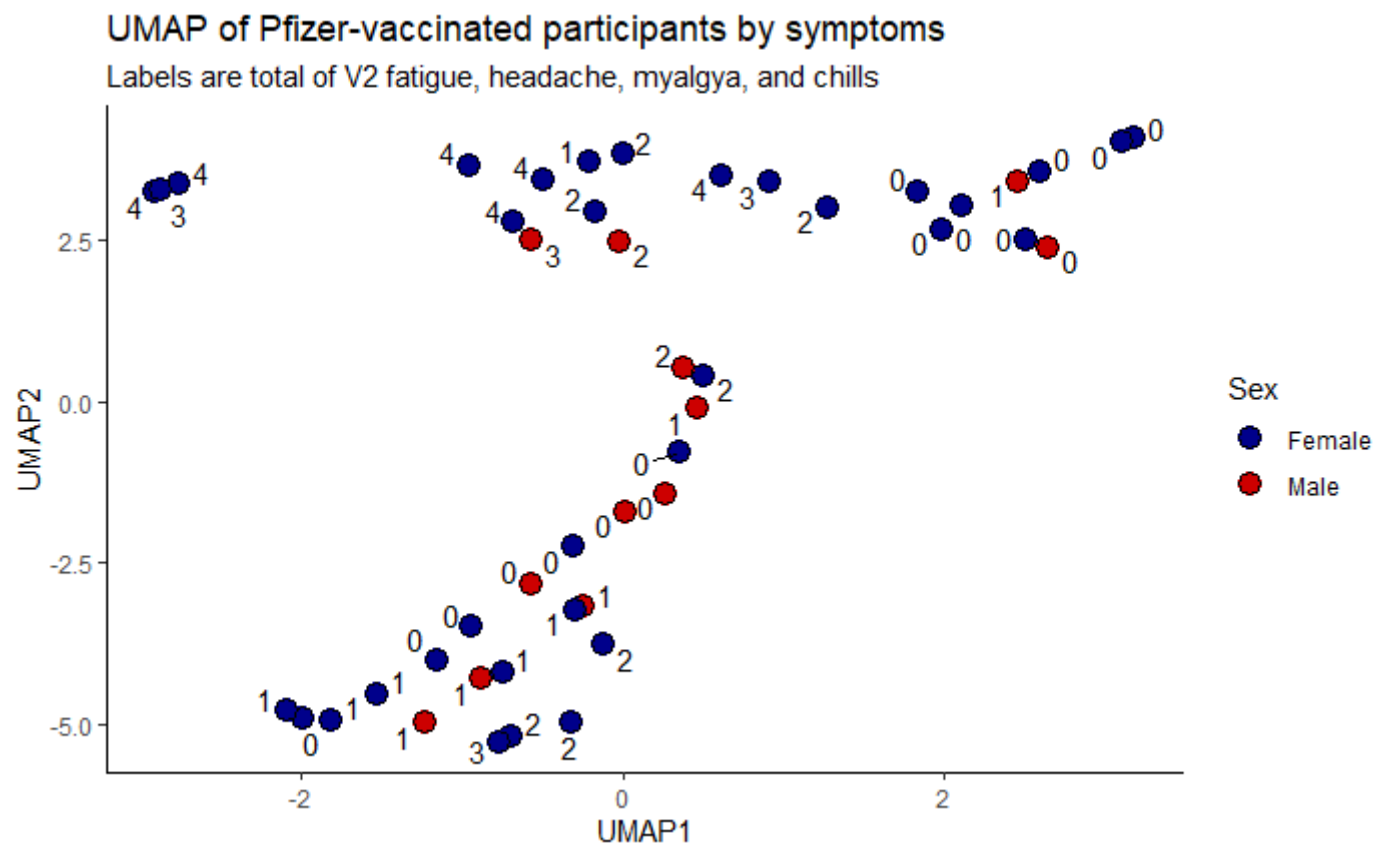
Data from Pfizer-vaccinated participants only (i.e., first and second dose) was used in this analysis due to the greater abundance and variety of V2 symptoms, and due to the small number of AstraZeneca-vaccinated participants.

In the clustered heatmap below we can see that there are broadly two groups of participants - those with V2 fatigue, headache, myalgia, and chills (right half), and those without (left half).

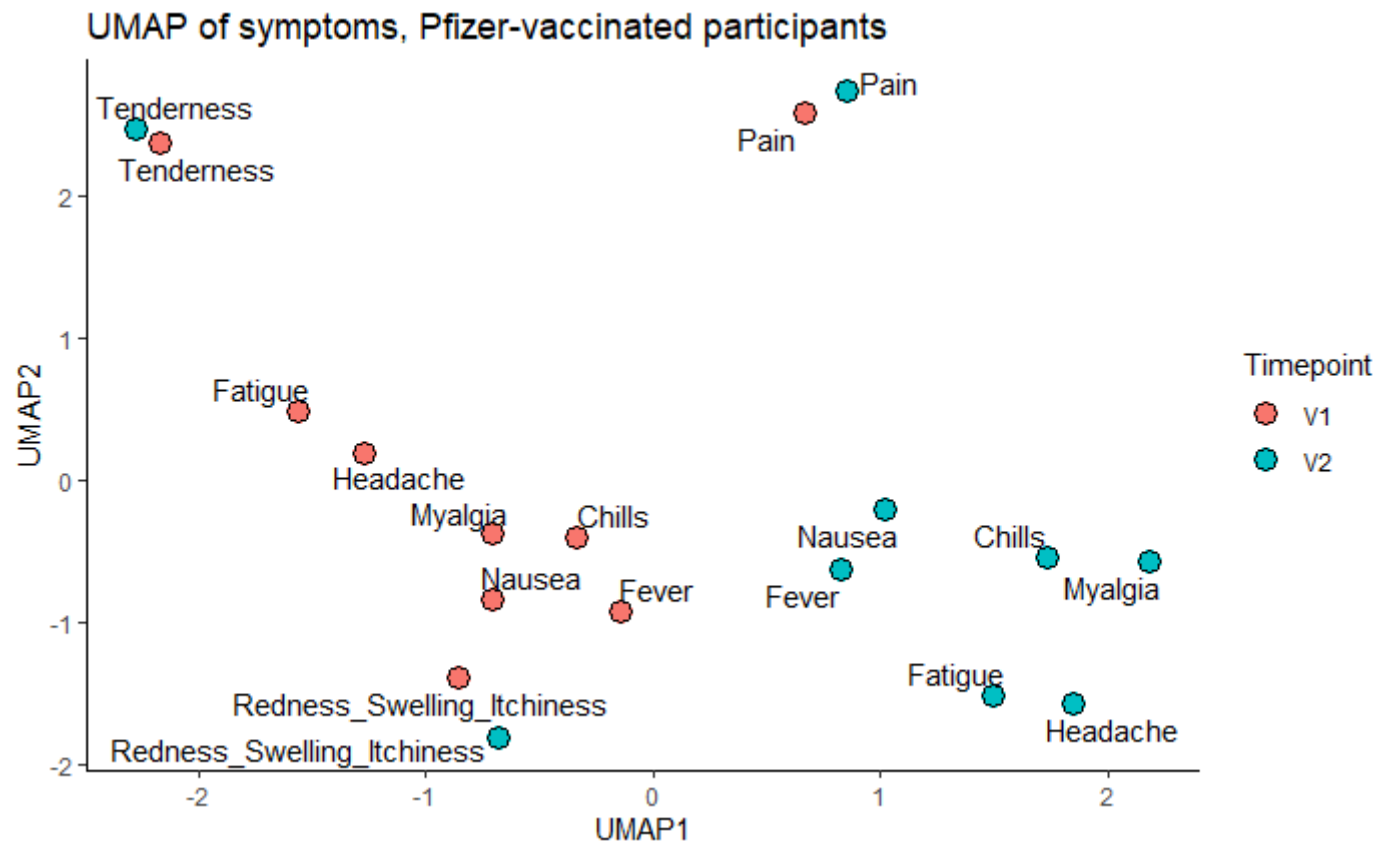


The below two plots are UMAPs of participants by symptoms (each point represents one person). We can see that there are two clusters within the emerging symptomatic group: the top cluster centered approximately at $(-0.5, 2.5)$ and the bottom cluster, centred approximately at $(-1, -5)$. The point labels showing total number of symptoms suggest that they differ in the presence (top cluster) or absence (bottom cluster) of fever and nausea in addition to the other systemic symptoms at V2. This heterogeneity was not accounted for in the differential expression (DE) analysis to follow due to the low sample size and hence low statistical power to confirm differences between these groups.

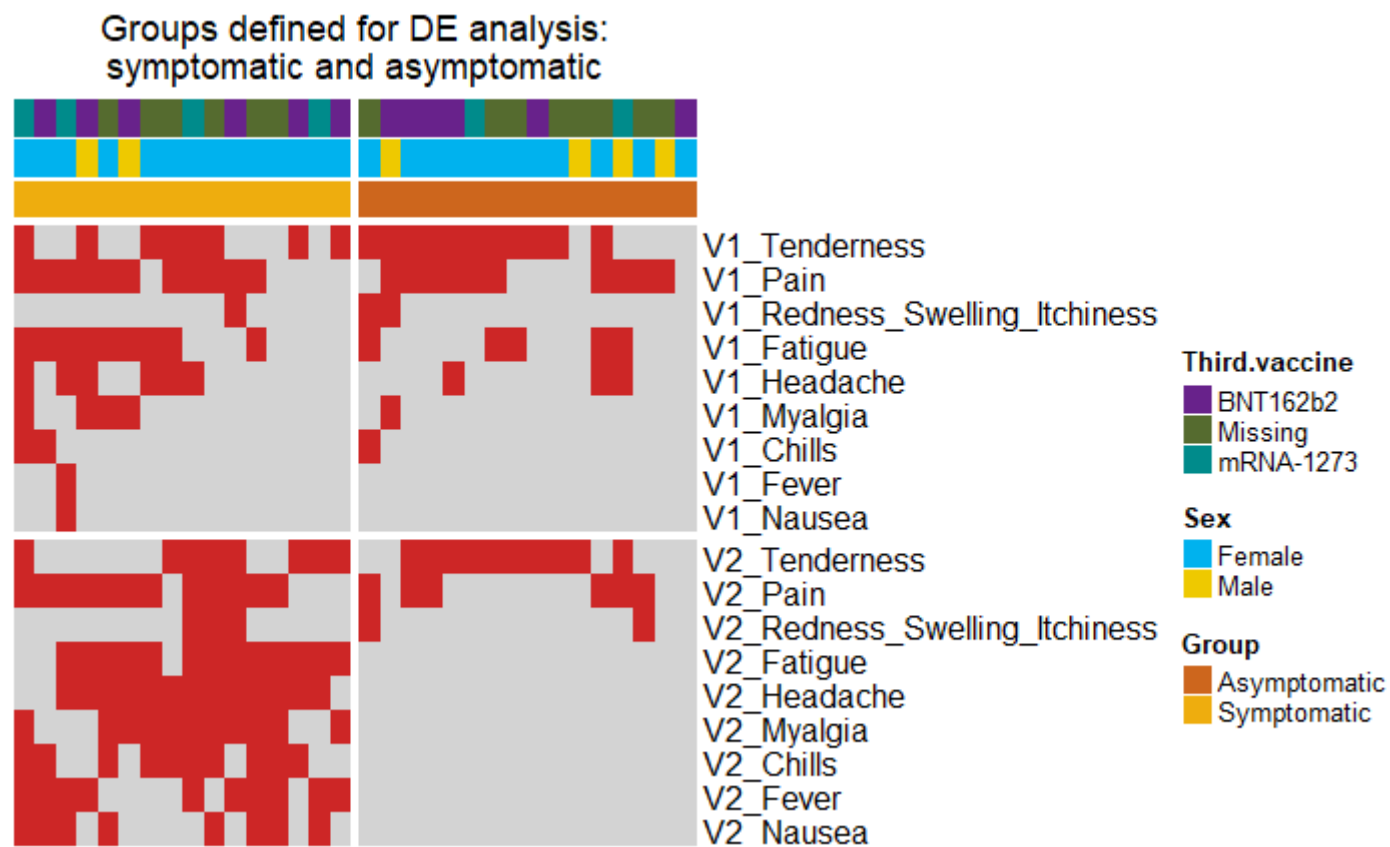




The UMAP below is a transpose of the above: each point here is a symptom. Immediately, we can see that local symptoms (pain, tenderness, and possibly redness/swelling/itchiness) cluster strongly together at both timepoints and are separated from the systemic symptoms. Note that nausea clusters together with the other systemic symptoms.



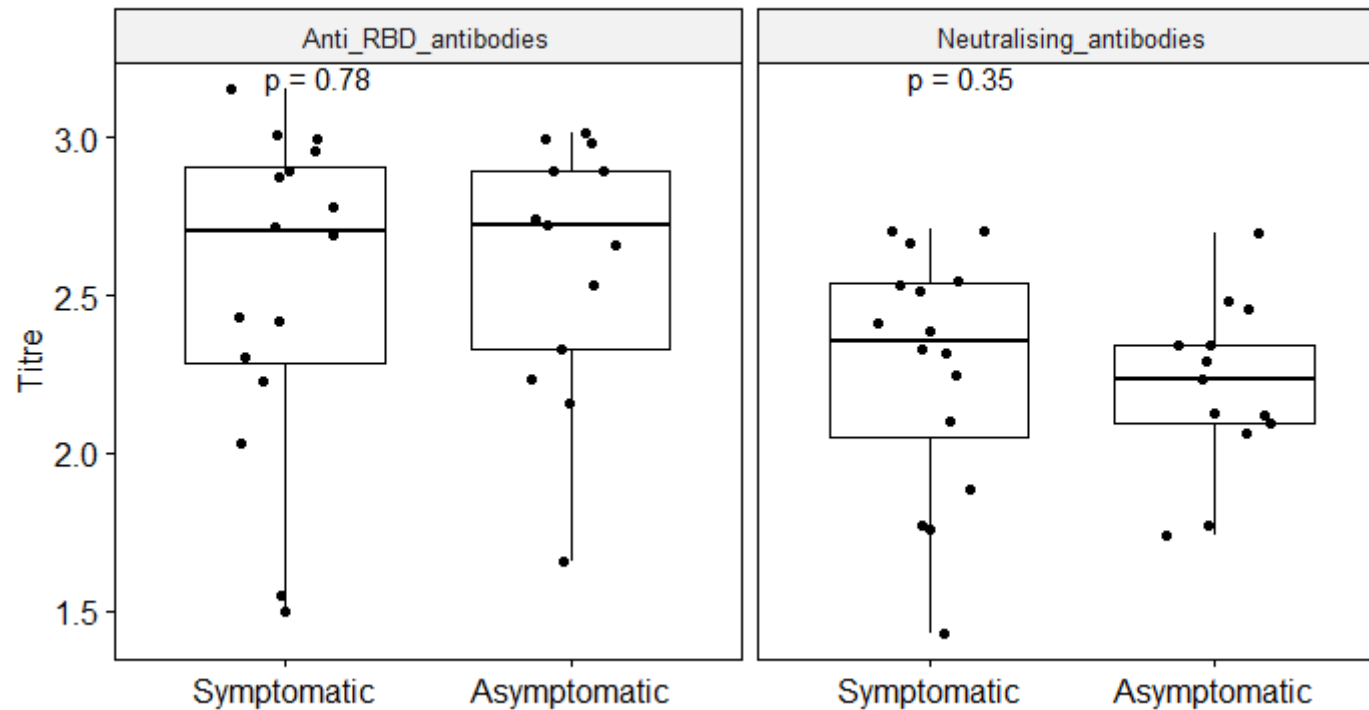
Finally, we can define comparison groups for DE analysis. Having 3 or more of V2 Fatigue, Headache, Myalgia, Chills, Fever, or Nausea (systemic symptoms) defines the symptomatic group ($n = 16$, 2 males). Having no V2 systemic symptoms and 2 or less of V2 Pain, Tenderness, or Redness/swelling/itchiness defines the asymptomatic group ($n = 16$, 4 males). There were many more females than males in the COVIRS dataset, so this is not surprising, and Fisher's exact test (not shown) indicates that this group composition is consistent with equal distribution ($p = 0.614$)



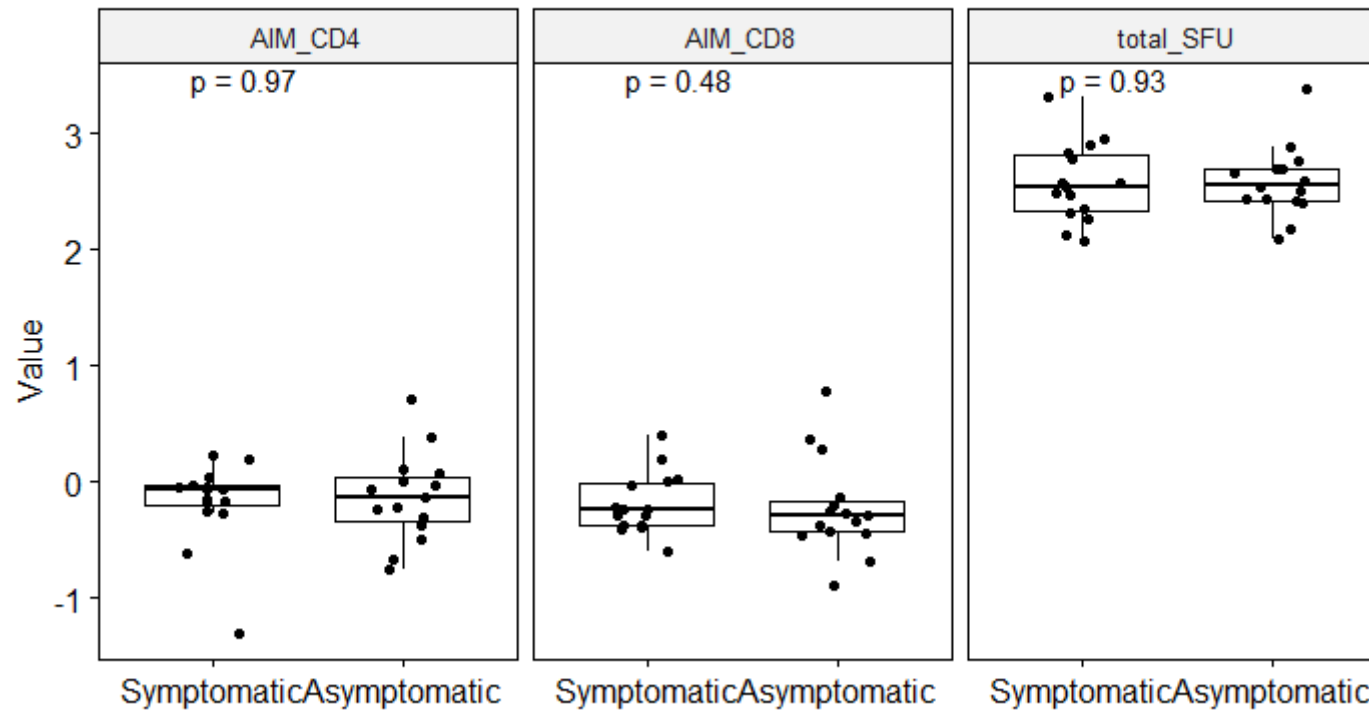
Antibodies and T cell responses

Another important motivator for this study is that the groups do not differ significantly in COVID antibody titres or T cell responses. This means that the symptoms observed do not correlate with common measures of vaccine effectiveness. Hence, this further motivates a DE analysis of the two groups.

COVID antibody titres are not significantly different
between symptomatic and asymptomatic groups at V2B



T cell responses are not significantly different
between symptomatic and asymptomatic groups at V2B

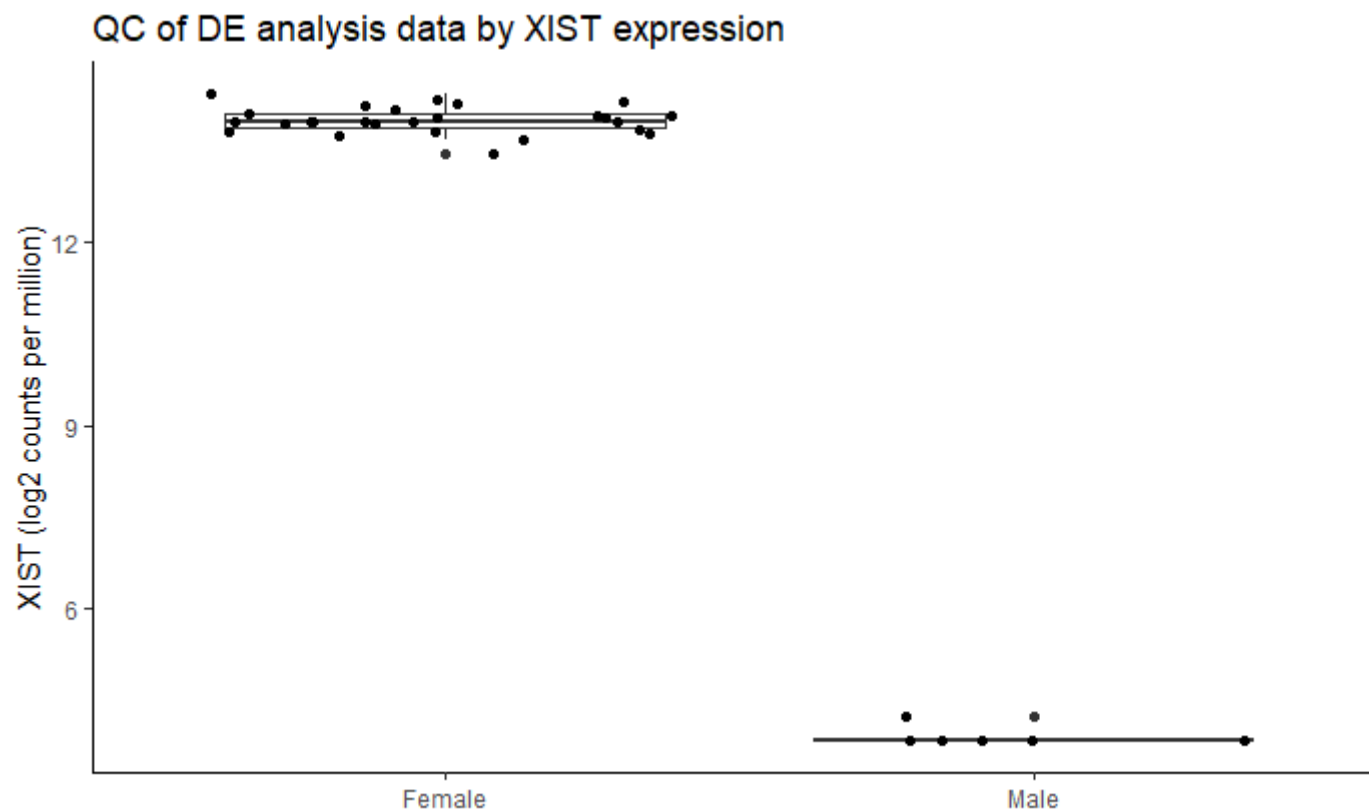


Flow cytometry

At V2, blood B cell count is significantly lower in the symptomatic group. This is explained by B cells migrating to the spleen to complete their development.

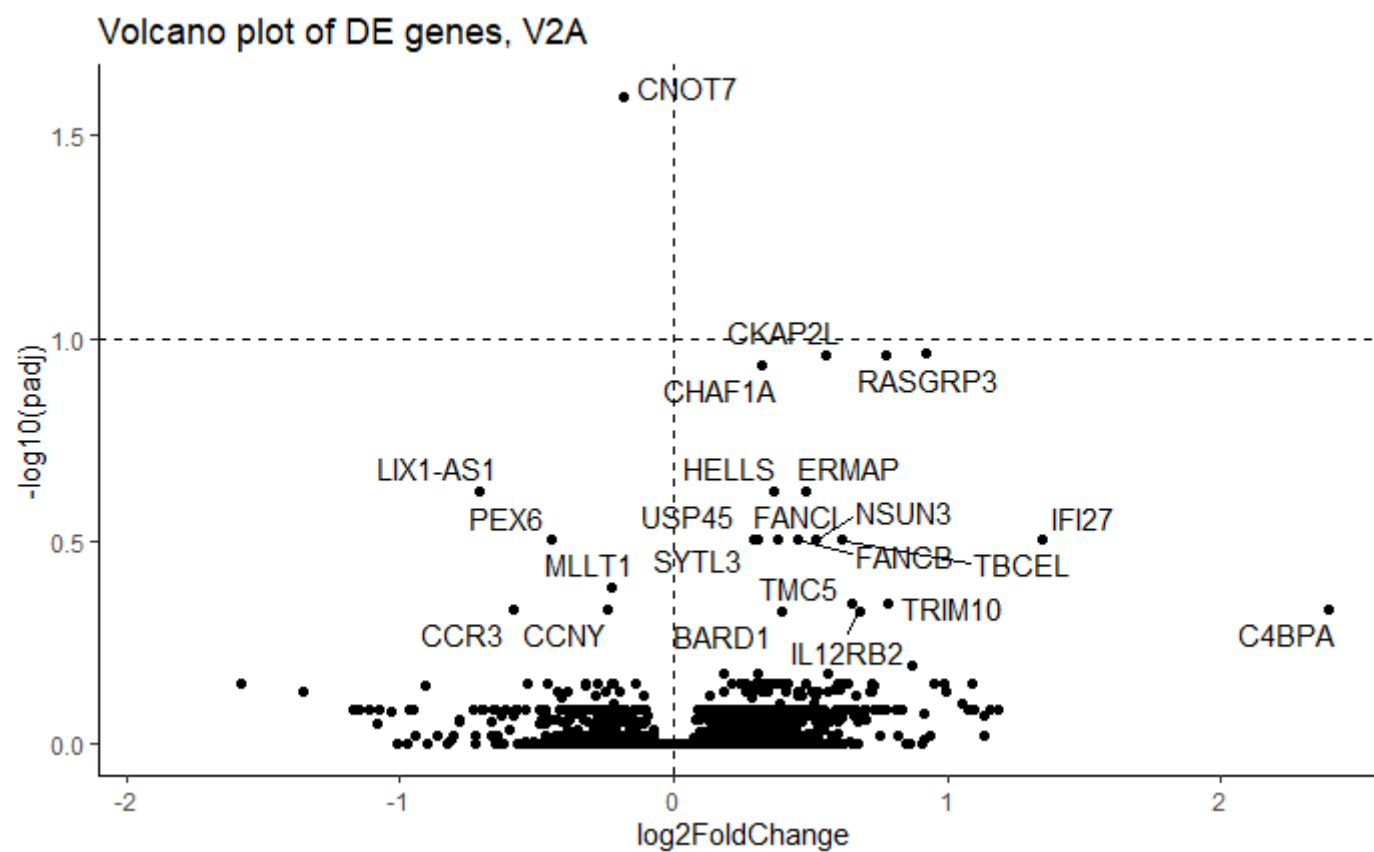


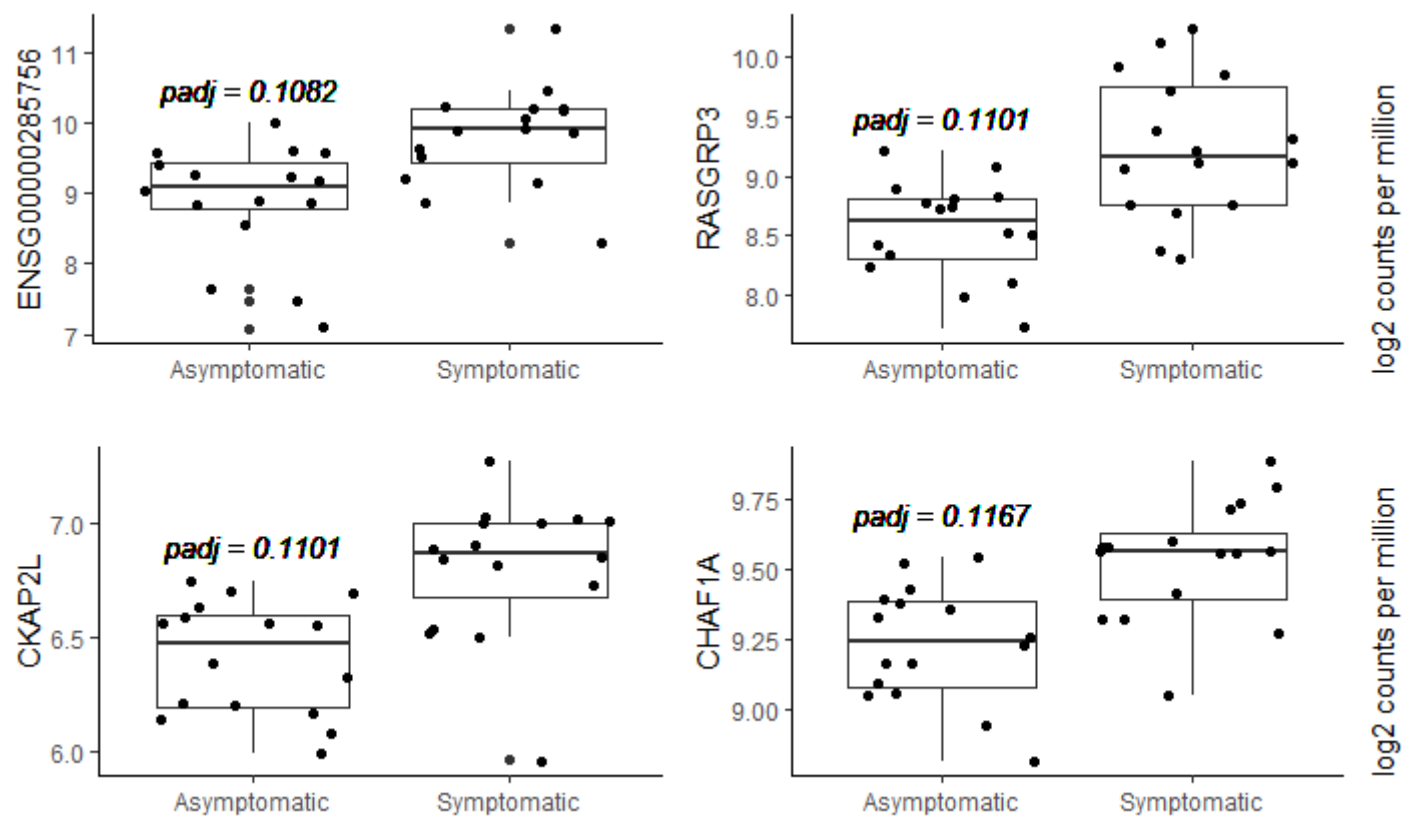
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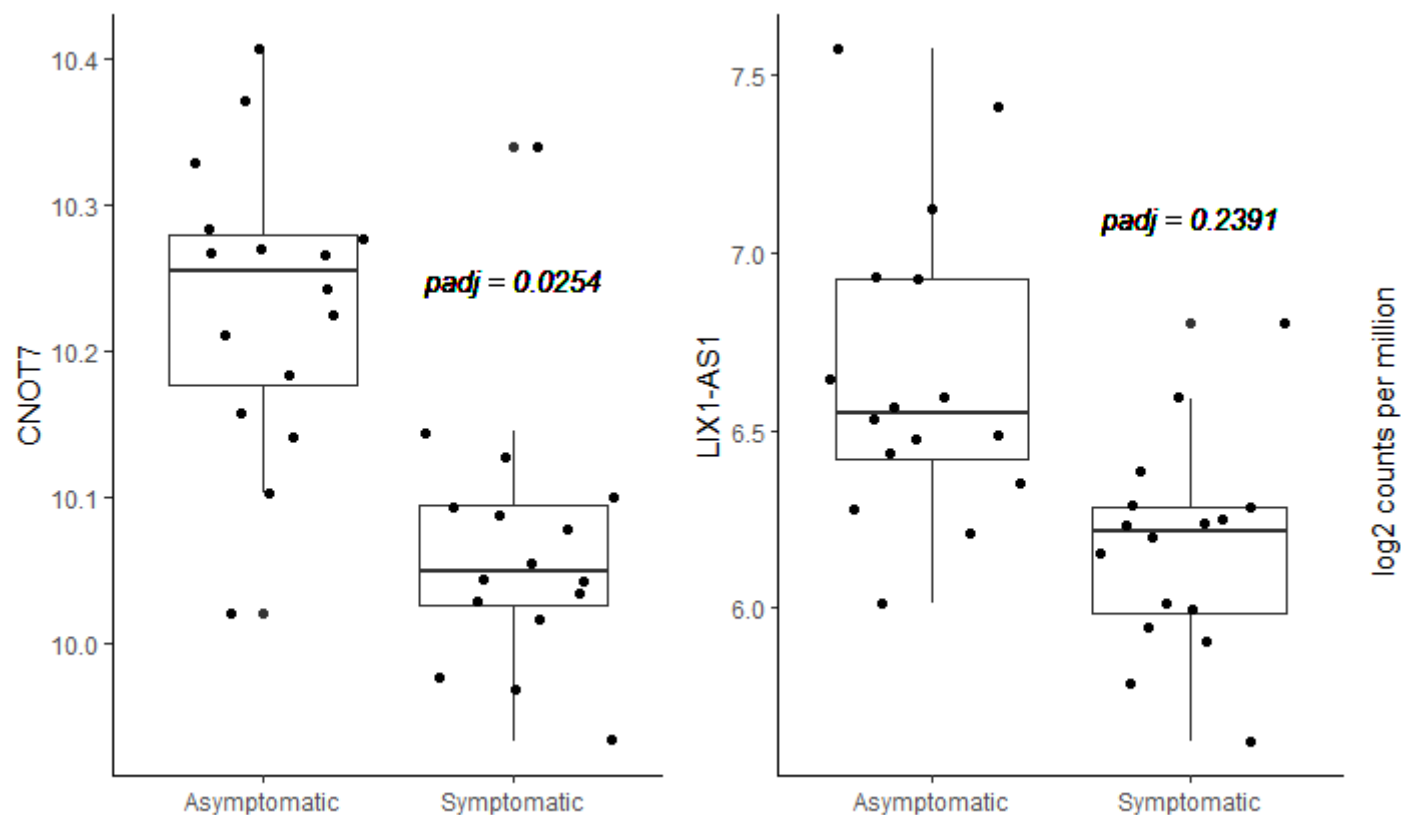


Only genes with 100 read counts or more in at least 4 samples (i.e., participants) were kept from the counts matrix, and DESeq2 (<https://bioconductor.org/packages/release/bioc/html/DESeq2.html>) was used to find differences between the groups while controlling for differences due to sex.

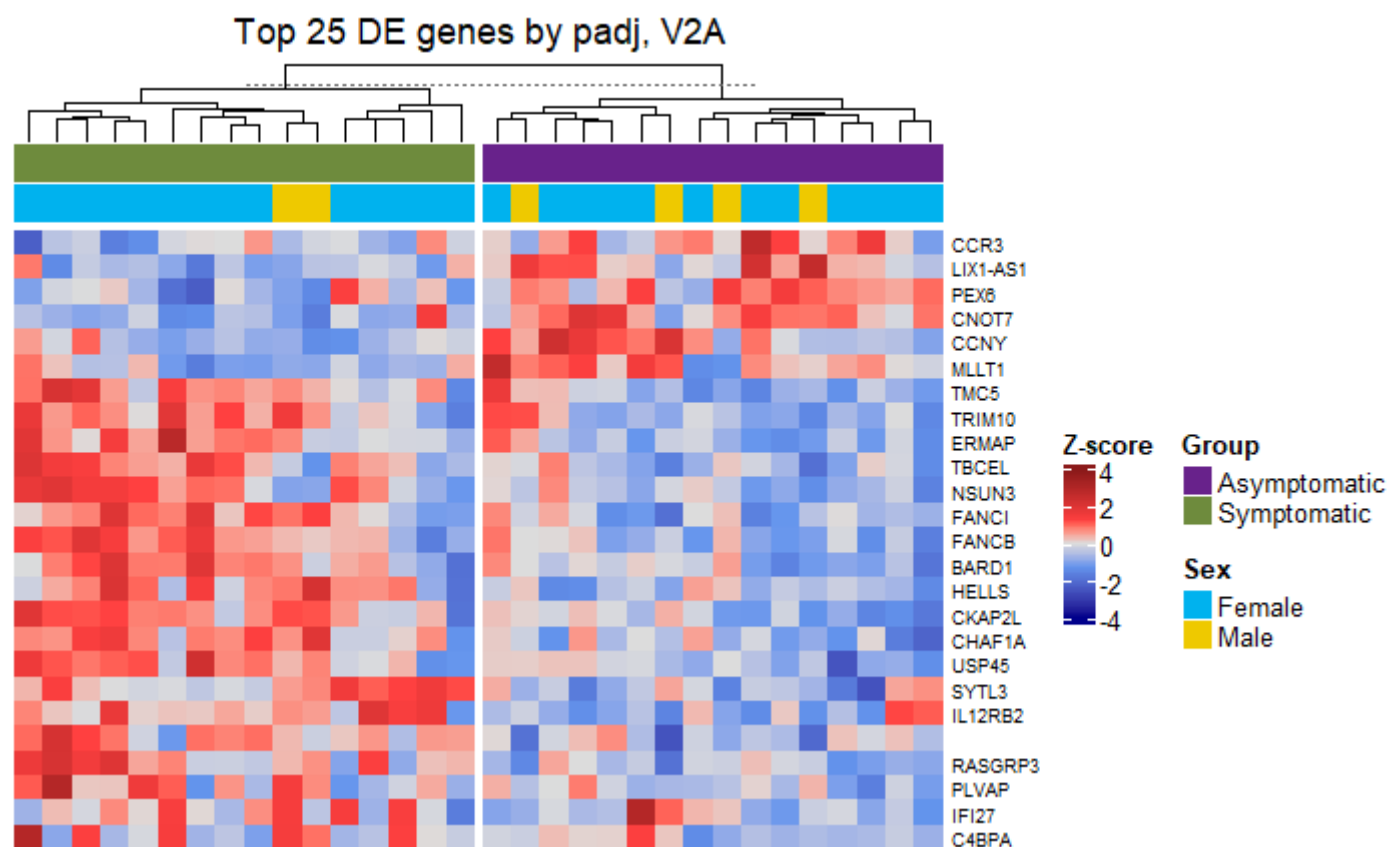
A few genes with positive log2 fold change (i.e., overexpressed in the symptomatic group) are approaching significance ($\text{padj} \leq 0.1$). Of genes with negative log2 fold change, only CNOT7 was significant.







CNOT7 depletion was reported by Ren et al. (2020) (<https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7193174/>) and Guo et al. (2019) (<https://pesquisa.bvsalud.org/porta1/resource/pt/wpr-744830>) to reduce TGF beta 1 production in liver cancer cells and, importantly, increase IFN gamma secretion by NK cells. Are these cells more active in the symptomatic participants? To answer this and other questions about the immune response, and to find expression differences in groups of genes rather than individual genes, a gene set enrichment analysis was conducted.

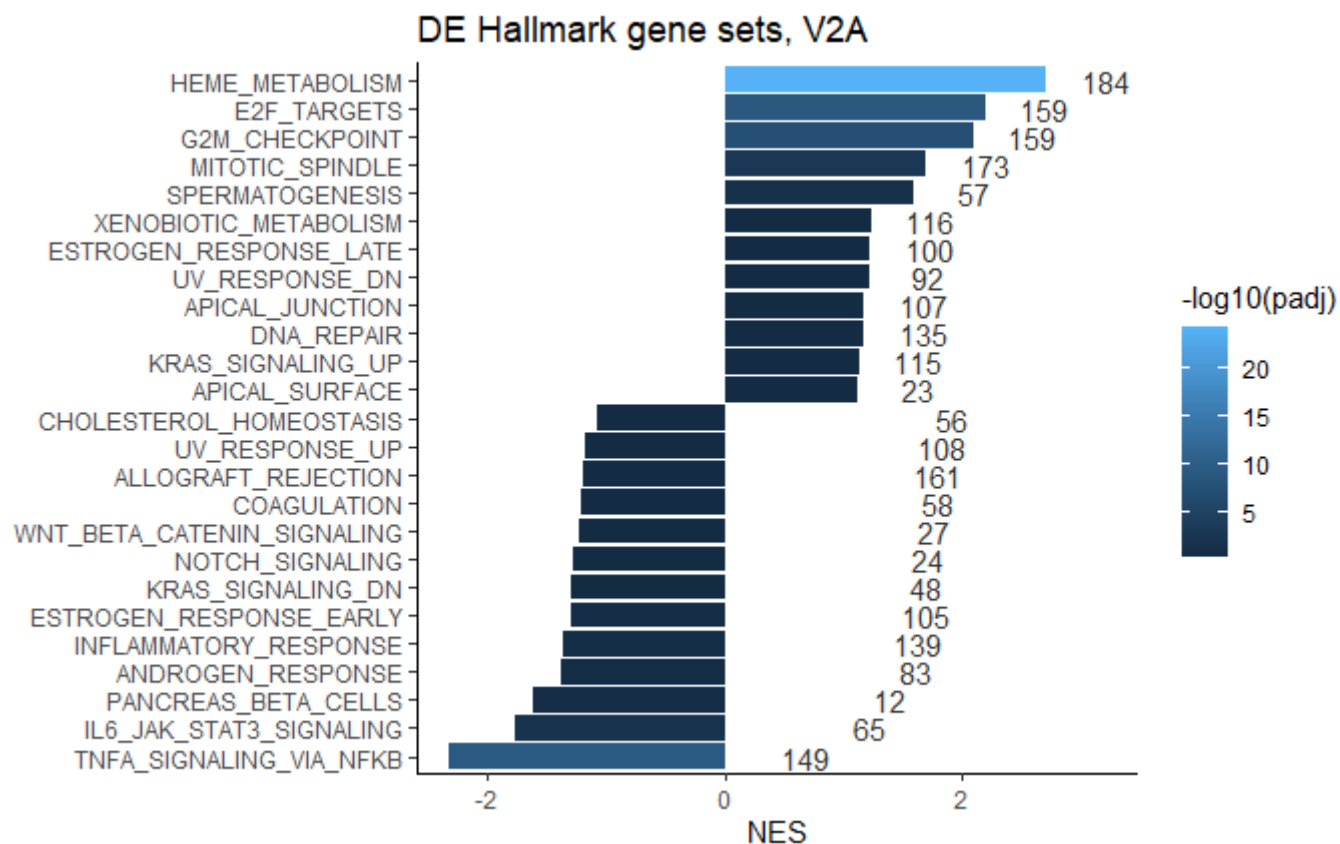


fgsea (<https://bioconductor.org/packages/release/bioc/html/fgsea.html>) with MSigDB (http://www.gsea-msigdb.org/gsea/msigdb/human/collection_details.jsp) gene sets was used to conduct GSEA. For the symptomatic group, two differentially expressed Hallmark gene sets are of interest: an increase in the expression of heme metabolism genes, and a decrease in TNFa signalling genes. However, there is a significant decrease in B cell count in the symptomatic group, suggesting that the “enrichment” in heme metabolism genes is merely an artefact of the increased proportion of RBCs and erythroblasts in this group.

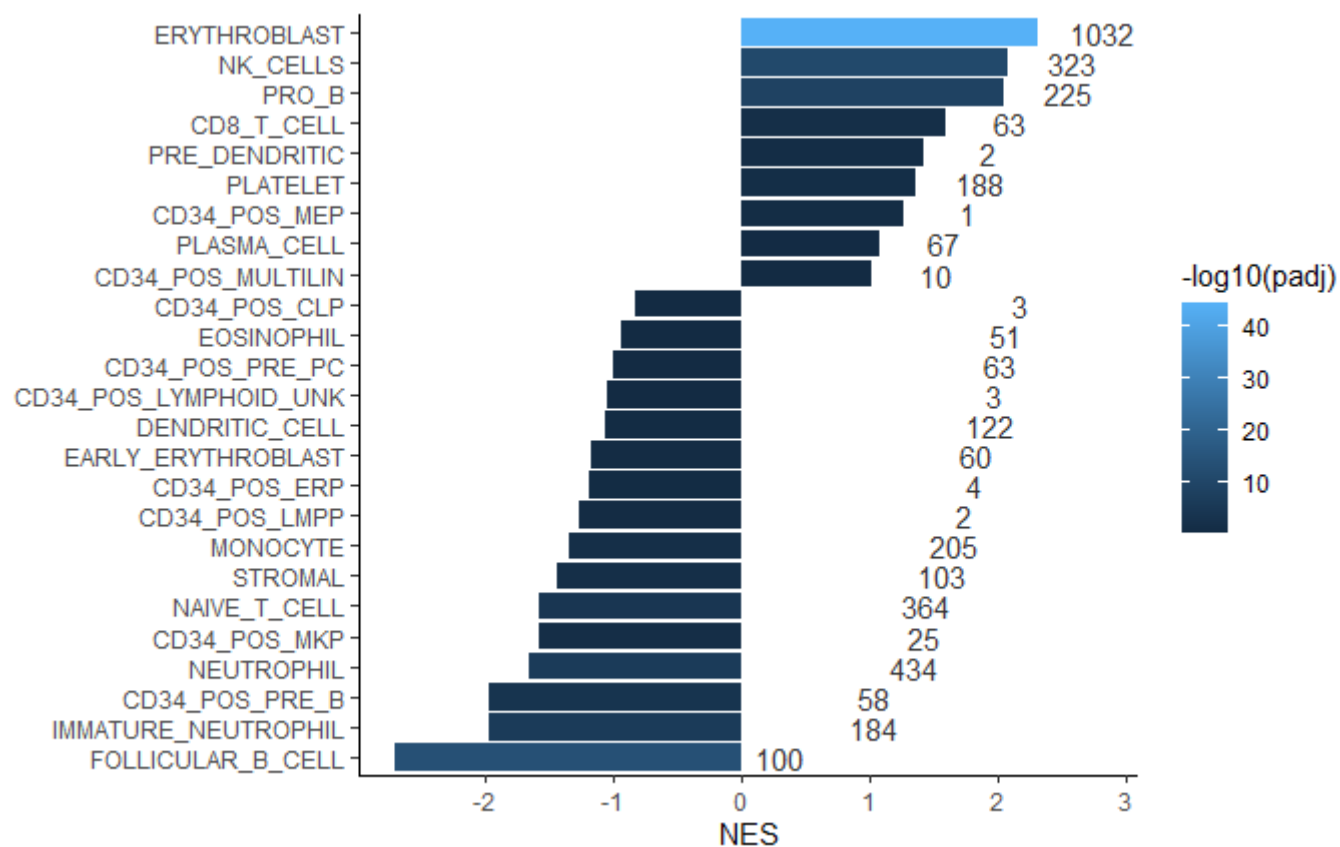
As for TNFa signalling, scanning the Human Protein Atlas for single-cell expression of NFKB1 (<https://www.proteinatlas.org/ENSG00000109320-NFKB1/single+cell+type>) and TNF (<https://www.proteinatlas.org/ENSG00000232810-TNF/single+cell+type>) in B cells suggests that these proteins are not overexpressed in this cell type compared to other immune cells, and hence the decrease in TNFa pathway gene expression is likely not an artefact.

An important note for interpreting volcano plots of gene sets: most of the time, individual genes are *not* differentially expressed with a sufficient padj

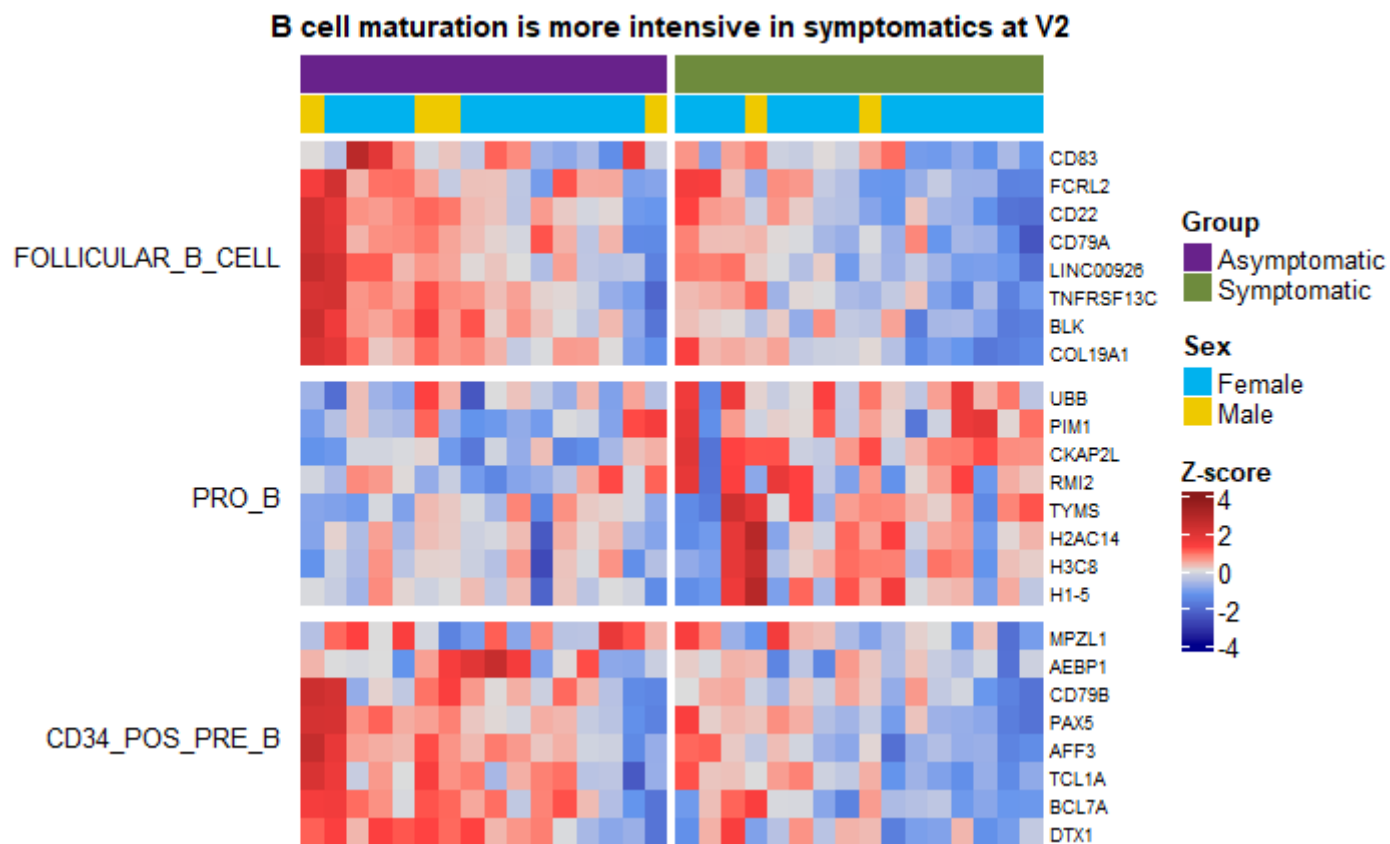
(whose value is very low in most cases). These plots are shown to illustrate the very different shapes of the data that are nonetheless assigned similar normalised expression scores and padj values by fgsea.



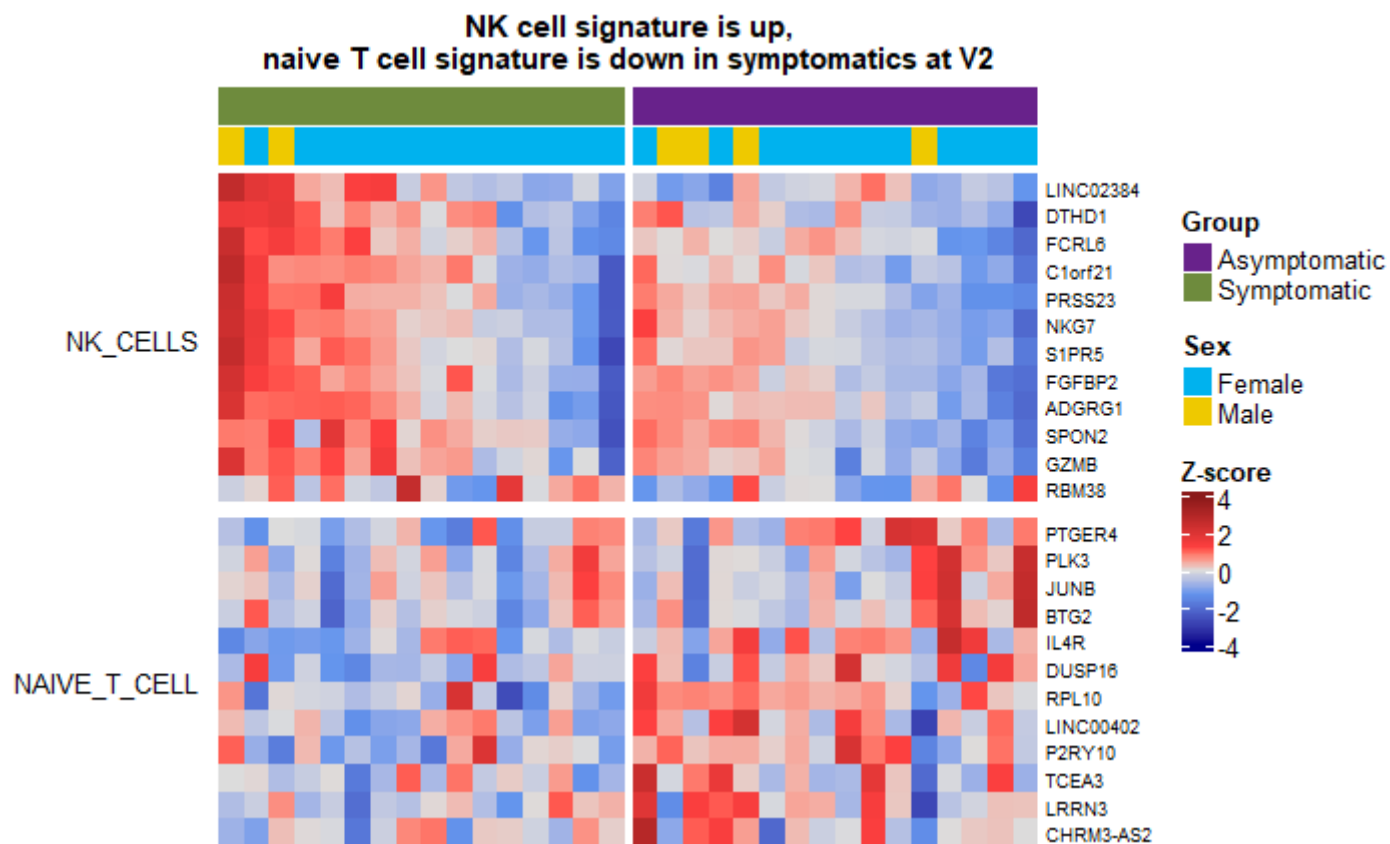
Next, bone marrow gene sets from Hay et al., 2018 (<https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6296228/>) were used to find cell type signatures differentially expressed between the two groups. Once again, erythroblast genes are very strongly and confidently “turned up”, likely an artifact of the increased proportion of erythroblasts.



Taken together, the three significant B cell signatures indicate more intensive B cell maturation in the symptomatic group: there is a stronger signature of early (Pre-B) cells in the blood, and a weaker blood signature of B cell stages expected to migrate into lymph.

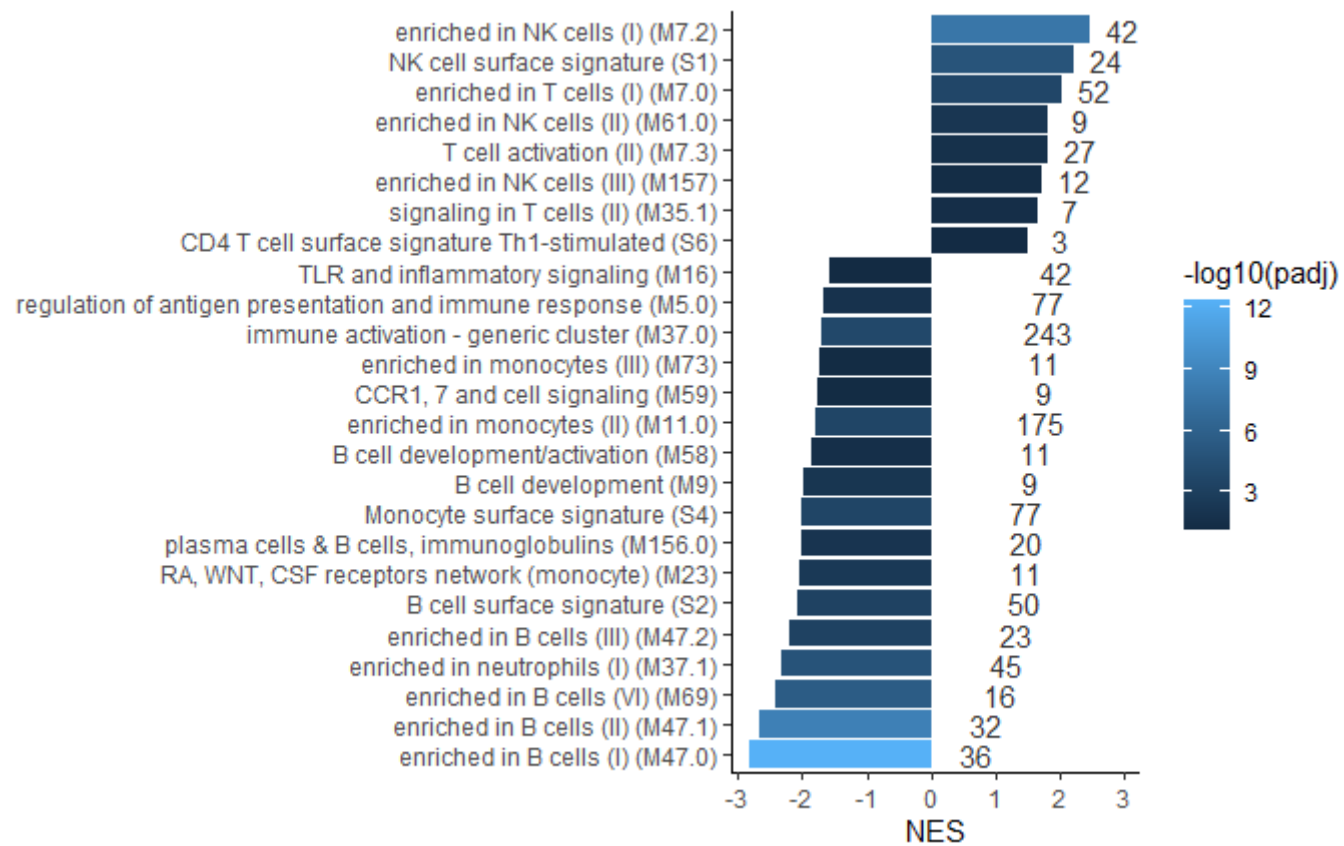


As expected from the significantly reduced expression of CNOT7, there is a stronger NK cell signature in the symptomatic group (i.e., the cells are more active, as the counts are not significantly different between the groups). Interestingly, the naive T cell signature is down, suggesting that T cells are also further differentiated in the symptomatic group, although there is no corresponding mature T cell signature to support this.

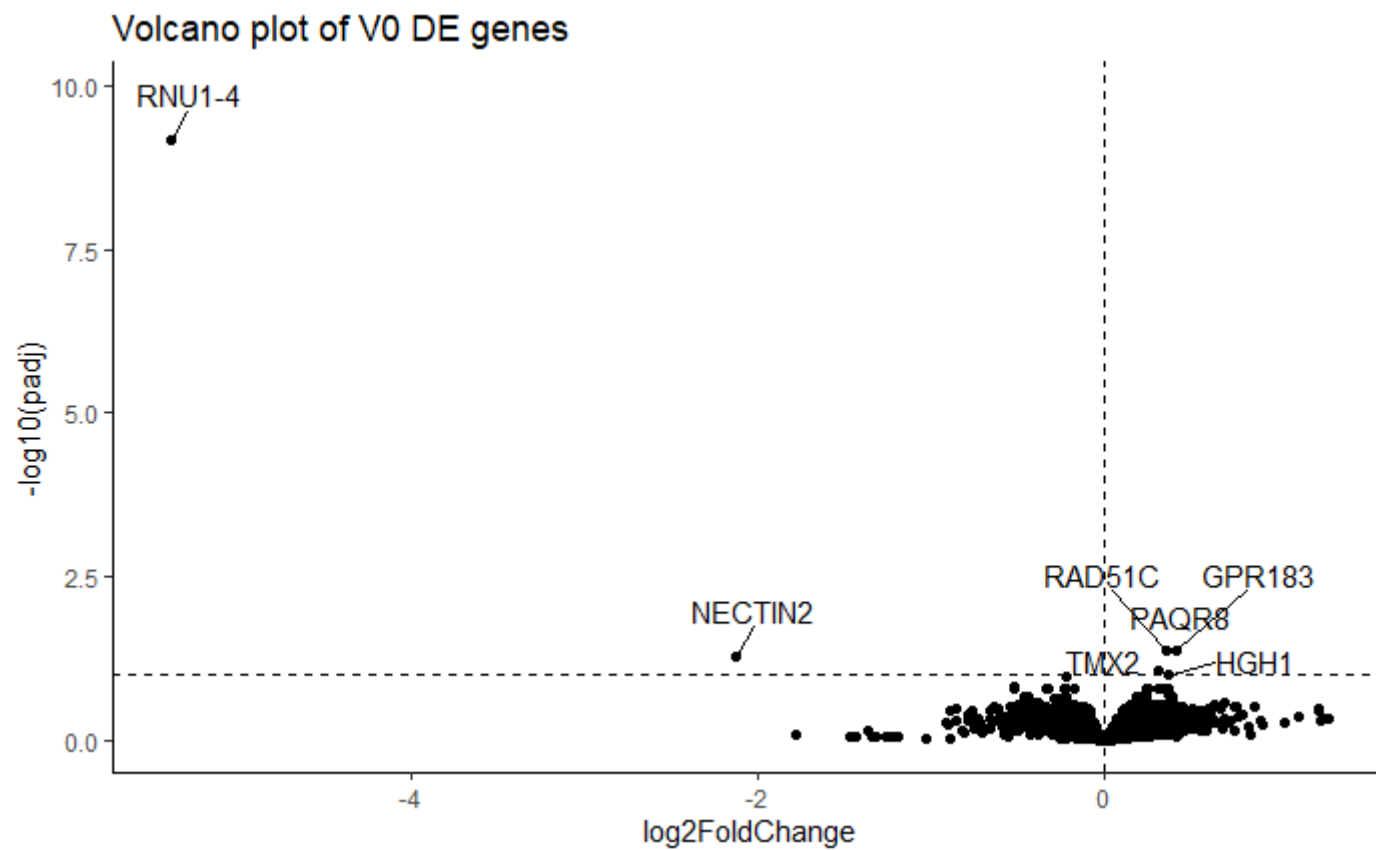


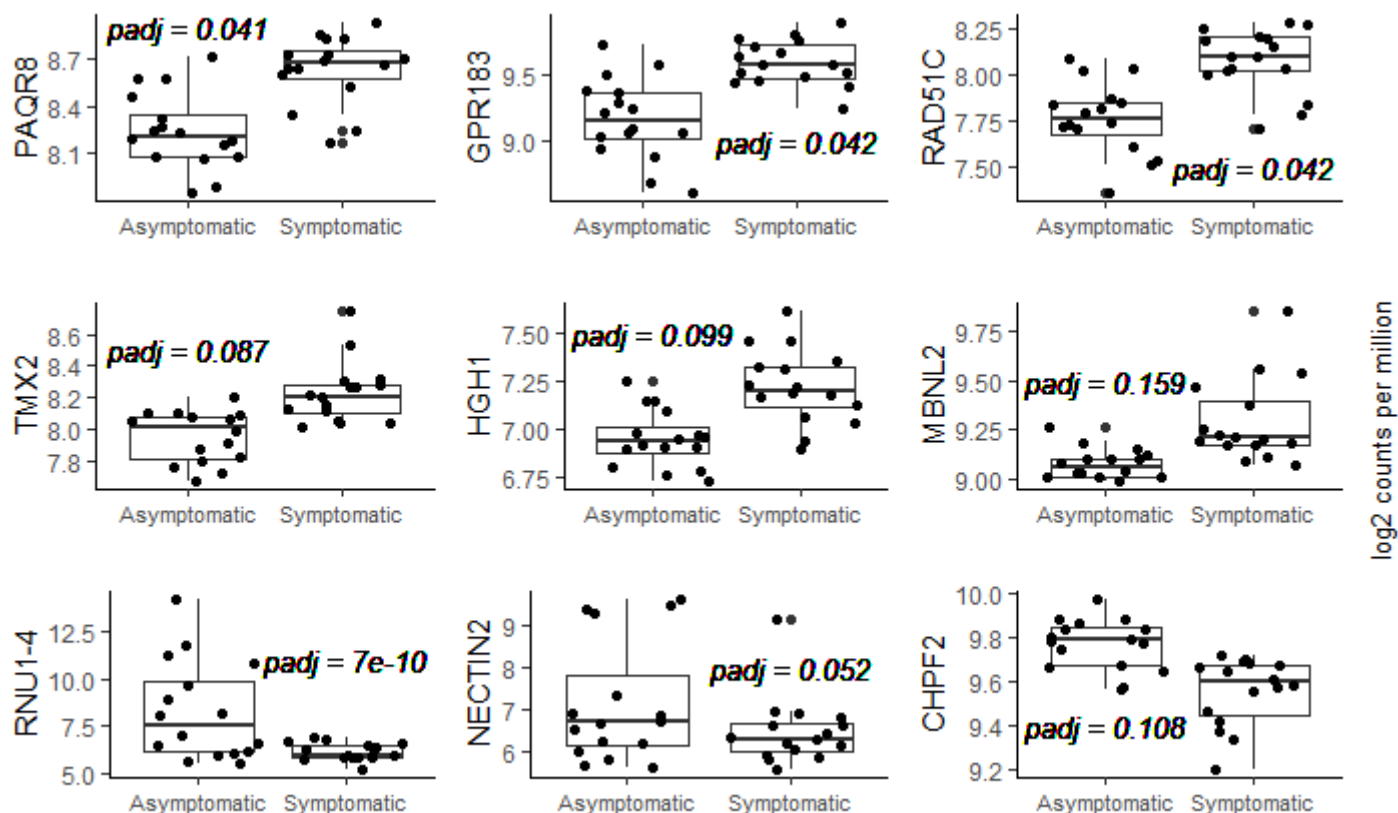
The neutrophil signatures observed above have to be treated separately. The volcano and enrichment plots below show that, unlike NK/B/T cell signatures above, the distribution of genes by padj and $\log_2\text{FoldChange}$ does not convincingly agree with the NES value for these gene sets.

GSEA with blood transcriptional modules (BTMs) mostly confirms these findings. B cell signature is down in the symptomatic group, agreeing with flow data, and NK cells are more active. The idea that T cells are also differentiating more intensively is supported here (enriched in T cells module). Finally, the reduced neutrophil signature is more solid with BTMs, but the reduced monocyte signature is dubious and only included for reference.



V0 GSEA





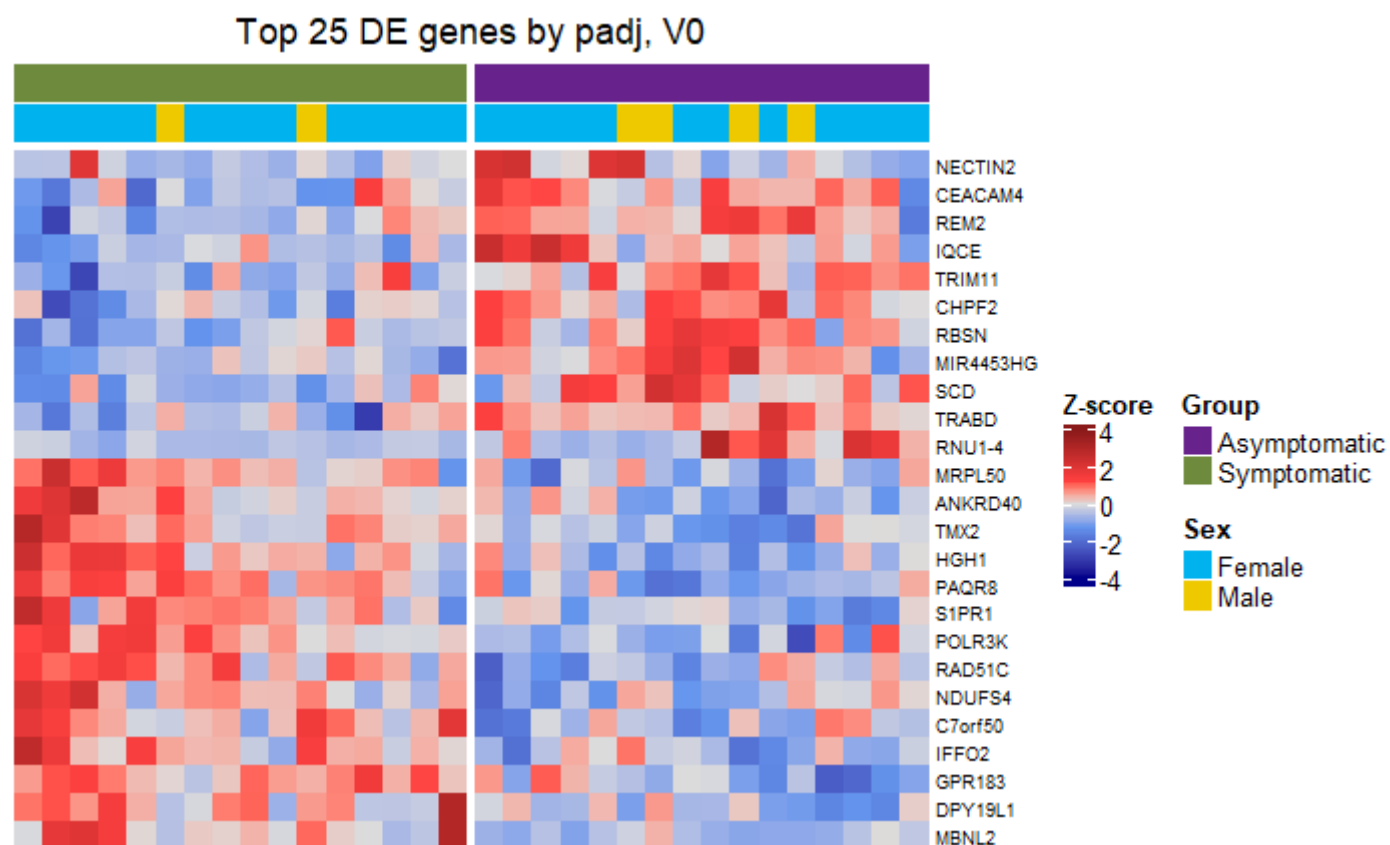
PAQR8: Groh et al. (2022) (<https://doi.org/10.1002/jlb.3ab1220-846r>) find that progesterone receptor activates monocyte immunity trained by LDLs

GPR183: required for immune cell maturation through oxysterol chemotaxis in lymph nodes (Daugvilaite et al., 2014) (<https://doi.org/10.1002/eji.201444493>)

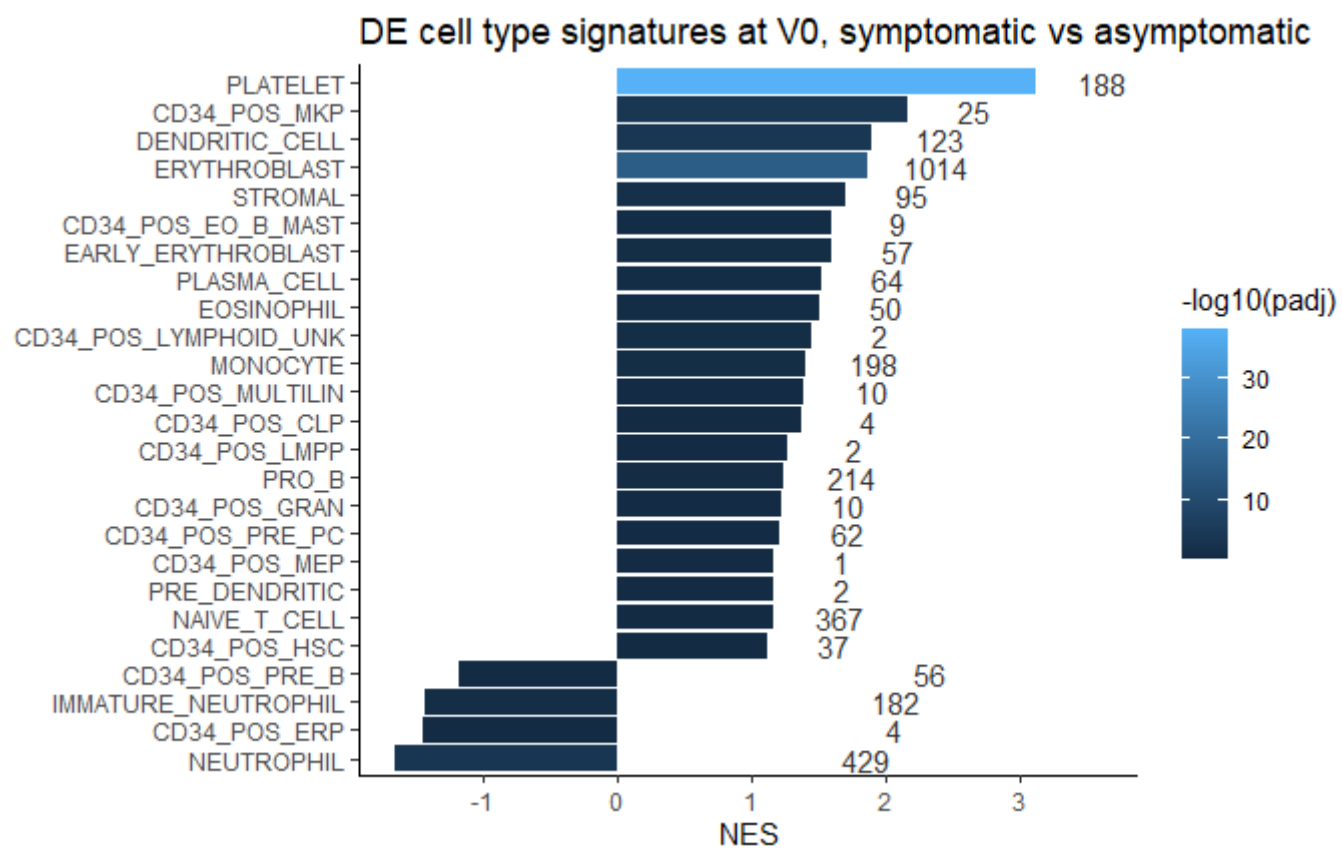
RAD51C: linked to poor ovarian cancer prognosis, no clear link with immune system (Lu et al., 2020) (<https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7013370/>)

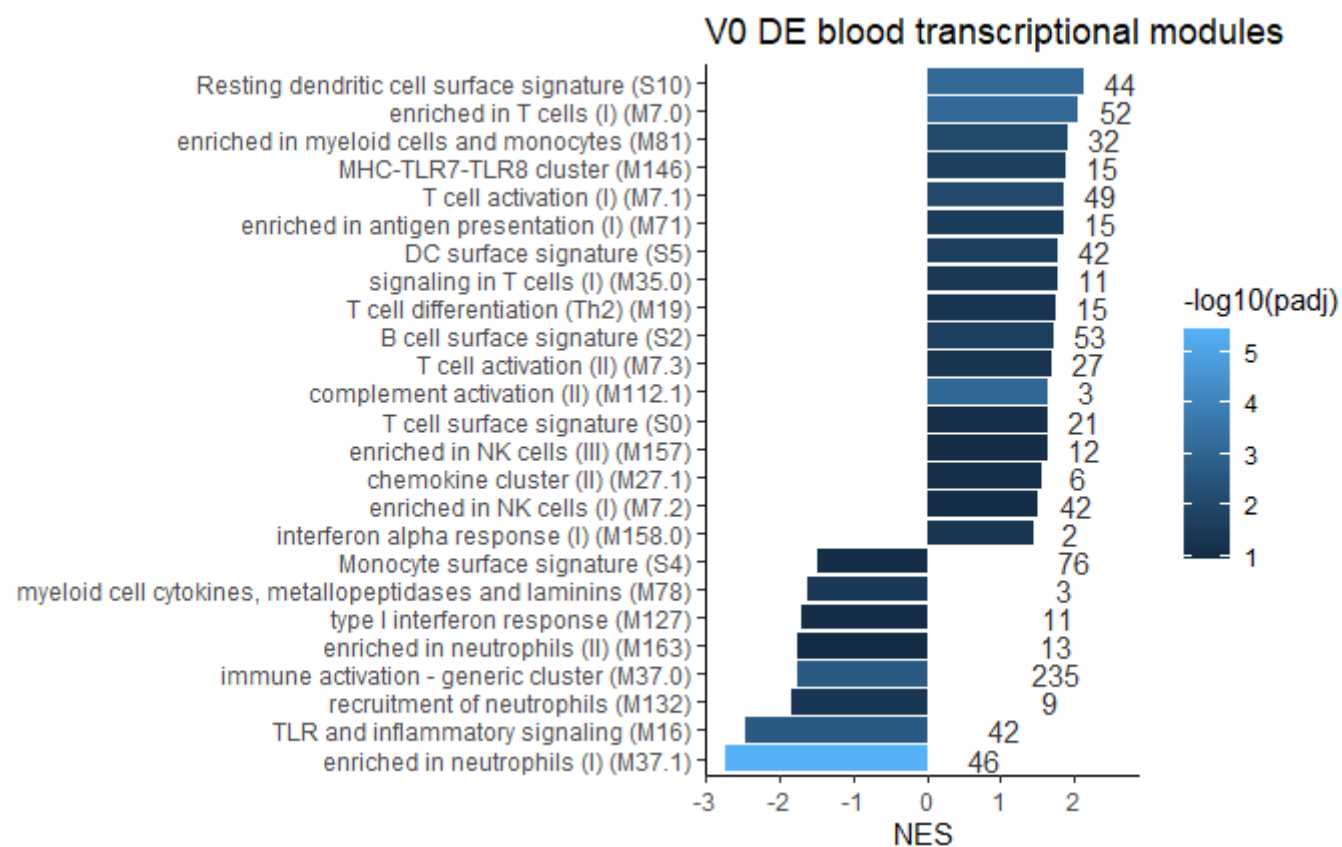
NECTIN2: bound by inhibitory T cell receptor (Deuss et al., 2017) (<https://doi.org/10.1074/jbc.m117.786483>)

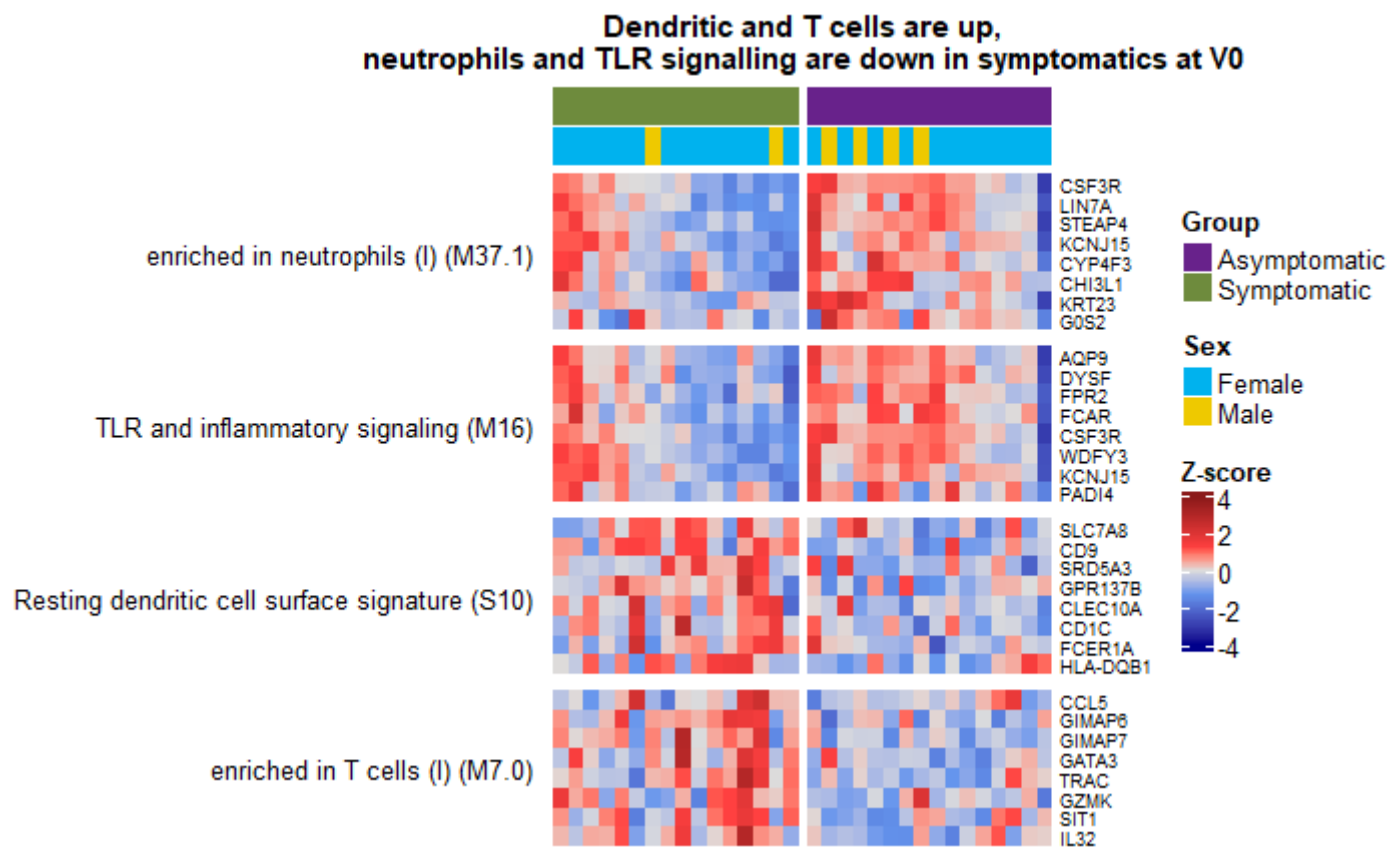
RNU1-4: no clear function or useful references from GeneCards (<https://www.genecards.org/cgi-bin/carddisp.pl?gene=RNU1-4>)



An increased dendritic cell signature in the symptomatic group is found by FGSEA using both MSigDB and BTMs. Takano et al. (2020) (<https://doi.org/10.1016/j.xcrm.2022.100631>) found that NK and dendritic cell migration occurs in the first day after Pfizer vaccination and correlates with local and systemic adverse events, suggesting that the increased BTM signature in this study may be predictive of this migration in the symptomatic group. V2 samples were collected 28 days after the second dose, and the increased blood NK signature suggests that these cells migrate back into the blood in the symptomatic group.







Summary

This study tentatively suggests that, after the second dose, individuals with strong adverse reactions to the Pfizer COVID vaccine have reduced blood RNAseq signatures of NK cells (possibly with reduced activity via CNOT7 underexpression and stronger TNFa signalling) and a significantly lower blood B cell count (possibly due to migration into the lymph for maturation).

There is evidence that early NK and dendritic cell migration to the site of inflammation correlates with symptom severity, suggesting that the increased signature reflects NK cell return to the blood, although this is not seen in flow cytometry data.

Prior to vaccination, these individuals have increased signatures of dendritic and T cells, suggesting higher baseline activity, and a reduced neutrophil signature. They also underexpress RNU1-4, a small RNA with no known function.

References

- Daugvilaite, V., Arfelt, K. N., Benned-Jensen, T., Sailer, A. W., & Rosenkilde, M. M. (2014). Oxysterol-EBI2 signaling in immune regulation and viral infection. *European Journal of Immunology*, 44(7), 1904–1912. <https://doi.org/10.1002/eji.201444493>
- Deuss, F. A., Gully, B. S., Rossjohn, J., & Berry, R. (2017). Recognition of nectin-2 by the natural killer cell receptor T cell immunoglobulin and ITIM domain (TIGIT). *Journal of Biological Chemistry*, 292(27), 11413–11422. <https://doi.org/10.1074/jbc.M117.786483>
- Groh, L., Verel, D. E., Charlotte, Matzaraki, V., Netea, M. G., Charlotte, Valerie, Mourits, V. P., Keating, S. T., Puffelen, van, Leo, Netea, M. G., & Riksen, N. P. (2022). Immune modulatory effects of progesterone on oxLDL-induced trained immunity in monocytes. *Journal of Leukocyte Biology*, 112(2), 279–288. <https://doi.org/10.1002/jlb.3ab1220-846r>
- Guo, S., Zhao, H., Ren, X., Ren, C., He, J., & Zhao, H. (2019). Effect of CNOT7 Gene Knockdown on the Immune Microenvironment of HepG2 Cells by Reduced TGF- β 1 Secretion. *Journal of China Medical University*, 225–229. <https://pesquisa.bvsalud.org/portal/resource/pt/wpr-744830>
- Hay, S. B., Ferchen, K., Chetal, K., Grimes, H. L., & Salomonis, N. (2018). The Human Cell Atlas bone marrow single-cell interactive web portal. *Experimental Hematology*, 68, 51–61. <https://doi.org/10.1016/j.exphem.2018.09.004>
- Karlsson, M., Zhang, C., Méar, L., Zhong, W., Digre, A., Katona, B., Sjöstedt, E., Butler, L., Odeberg, J., Dusart, P., Edfors, F., Oksvold, P., von Feilitzen, K., Zwahlen, M., Arif, M., Altay, O., Li, X., Ozcan, M., Mardinoglu, A., & Fagerberg, L. (2021). A single-cell type transcriptomics map of human tissues. *Science Advances*, 7(31). <https://doi.org/10.1126/sciadv.abh2169>
- Li, S., Rouphael, N., Sai Duraisingham, Romero-Steiner, S., Presnell, S. R., Davis, C. W., Schmidt, D., Johnson, S. P., Milton, A. S., Gowrisankar Rajam, Sudhir Pai Kasturi, Carlone, G. M., Quinn, C., Chaussabel, D., Karolina Palucka, Mulligan, M. J., Ahmed, R., Stephens, D. J., Nakaya, H. I.,

& Bali Pulendran. (2014). Molecular signatures of antibody responses derived from a systems biology study of five human vaccines. *Nature Immunology*, 15(2), 195–204. <https://doi.org/10.1038/ni.2789>

Love, M. I., Huber, W., & Anders, S. (2014). Moderated estimation of fold change and dispersion for RNA-seq data with DESeq2. *Genome Biology*, 15(12). <https://doi.org/10.1186/s13059-014-0550-8>

Lu, X.-L., Liu, S.-S., Xiong, Z.-F., Wang, F., Li, X.-Y., & Deng, H. (2020). Clinical significance of RAD51C and its contribution to ovarian carcinogenesis. *International Journal of Clinical and Experimental Pathology*, 13(1), 14–20. <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7013370/>

Mootha, V. K., Lindgren, C. M., Eriksson, K.-F., Subramanian, A., Sihag, S., Lehar, J., Puigserver, P., Carlsson, E., Ridderstråle, M., Laurila, E., Houstis, N., Daly, M. J., Patterson, N., Mesirov, J. P., Golub, T. R., Tamayo, P., Spiegelman, B., Lander, E. S., Hirschhorn, J. N., & Altshuler, D. (2003). PGC-1 α -responsive genes involved in oxidative phosphorylation are coordinately downregulated in human diabetes. *Nature Genetics*, 34(3), 267–273. <https://doi.org/10.1038/ng1180>

Ren, C., Ren, X., Cao, D., Zhao, H., Zhai, Z., Li, H., Li, Y., Fu, X., He, J., & Zhao, H. (2020). CNOT7 depletion reverses natural killer cell resistance by modulating the tumor immune microenvironment of hepatocellular carcinoma. *FEBS Open Bio*, 10(5), 847–860. <https://doi.org/10.1002/2211-5463.12836>

Ryan, F. J., Norton, T. S., McCafferty, C., Blake, S. J., Stevens, N. E., James, J., Eden, G. L., Yee Kai Tee, Benson, S. C., Makutiro Ghislain Masavuli, Eng, A., Arunasingam Abayasingam, Agapiou, D., Stevens, H., Zecha, J., Messina, N. L., Curtis, N., gnjatovic, V., Monagle, P., & Tran, H. (2022). A systems immunology study comparing innate and adaptive immune responses in adults to COVID-19 mRNA (BNT162b2/mRNA-1273) and adenovirus vectored vaccines (ChAdOx1-S) after the first, second and third doses. *MedRxiv* (Cold Spring Harbor Laboratory). <https://doi.org/10.1101/2022.09.22.22280180>

Sergushichev, A. A. (2016, June 20). An algorithm for fast preranked gene set enrichment analysis using cumulative statistic calculation. *BioRxiv*. <http://biorxiv.org/content/early/2016/06/20/060012>

Stelzer, G., Rosen, N., Plaschkes, I., Zimmerman, S., Twik, M., Fishilevich, S., Stein, T. I., Nudel, R., Lieder, I., Mazor, Y., Kaplan, S., Dahary, D., Warshawsky, D., Guan-Golan, Y., Kohn, A., Rappaport, N., Safran, M., & Lancet, D. (2016). The GeneCards Suite: From Gene Data Mining to Disease Genome Sequence Analyses. *Current Protocols in Bioinformatics*, 54(1), 1.30.1–1.30.33. <https://doi.org/10.1002/cpbi.5>

Subramanian, A., Tamayo, P., Mootha, V. K., Mukherjee, S., Ebert, B. L., Gillette, M. A., Paulovich, A., Pomeroy, S. L., Golub, T. R., Lander, E. S., & Mesirov, J. P. (2005). Gene set enrichment analysis: A knowledge-based approach for interpreting genome-wide expression profiles. *Proceedings of the National Academy of Sciences*, 102(43), 15545–15550. <https://doi.org/10.1073/pnas.0506580102>

Takano, T., Morikawa, M., Adachi, Y., Kiyomi Kabasawa, Sax, N., Moriyama, S., Sun, L., Masanori Isogawa, Nishiyama, A., Onodera, T., Kazutaka Terahara, Keisuke Tonouchi, Nishimura, M., Kentaro Tomii, Yamashita, K., Matsumura, T., Masaharu Shinkai, & Takahashi, Y. (2022). Distinct immune cell dynamics correlate with the immunogenicity and reactogenicity of SARS-CoV-2 mRNA vaccine. *Cell Reports Medicine*, 3(5),

100631–100631. <https://doi.org/10.1016/j.xcrm.2022.100631>