Single-cell RNA sequencing reveals ex vivo signatures of SARS-CoV-2-reactive T cells through ‘reverse phenotyping’

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The in vivo phenotypic profile of T cells reactive to severe acute respiratory syndrome (SARS)-CoV-2 antigens remains poorly understood. Conventional methods to detect antigen-reactive T cells require in vitro antigenic re-stimulation or highly individualized peptide-human leukocyte antigen (pHLA) multimers. Here, we use single-cell RNA sequencing to identify and profile SARS-CoV-2-reactive T cells from Coronavirus Disease 2019 (COVID-19) patients. To do so, we induce transcriptional shifts by antigenic stimulation in vitro and take advantage of natural T cell receptor (TCR) sequences of clonally expanded T cells as barcodes for ‘reverse phenotyping’. This allows identification of SARS-CoV-2-reactive TCRs and reveals phenotypic effects introduced by antigen-specific stimulation. We characterize transcriptional signatures of currently and previously activated SARS-CoV-2-reactive T cells, and show correspondence with phenotypes of T cells from the respiratory tract of patients with severe disease in the presence or absence of virus in independent cohorts. Reverse phenotyping is a powerful tool to provide an integrated insight into cellular states of SARS-CoV-2-reactive T cells across tissues and activation states.
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OVID-19 is a new form of viral pneumonia caused by SARS-CoV-2 and is affecting 67,073,749 patients, with 1,536,072 deaths, worldwide (source: Johns Hopkins University, as of December 7, 2020). Adaptive immunity is swiftly induced upon COVID-19 infection. T cells play a central role in this process and are implicated in contributing both to long-lasting immunity as well as to putative immunopathology. A thorough understanding of T cell responses to SARS-CoV-2 is therefore urgently needed.

Immunodominant SARS-CoV-2 antigen-specificities have been identified with unprecedented speed for an emerging pathogen, and phenotypic characterization of antigen-reactive T cells has quickly been performed by a plethora of studies. While there is general agreement that SARS-CoV-2-reactive T cells are activated and differentiate during the course of the immune response, the extent of activation and differentiation are controversial.

Vast resources of deeply profiled immune cells from COVID-19 patients do already exist and are bundled e.g., by the Human Cell Atlas initiative (www.humancellatlas.org). It is difficult, however, for any single study to cover different patient disease states and sample sites, together with detailed clinical metadata and deep profiling down to single-cell resolution, including antigen-specific analyses. For example, few studies have investigated T cell states across different tissue sites (e.g., from peripheral blood (PB) and the respiratory tract) in identical COVID-19 patients. Generally, antigen-specific T cells are expected to have different activation states in different tissues depending on the course of the disease. When a viral antigen is still present in the respiratory tract, T cells at the site of infection should show a more activated phenotype compared to PB T cells which are not being activated by the antigen at the time of analysis. In this context, difficulties to clearly define the phenotypic profile of currently and previously activated SARS-CoV-2-reactive T cells also hinder the precise contextualization of T cell signatures across publicly available data sets.

Methodologies for the characterization of antigen-reactive T cells differ and thereby obscure a clear insight into T cell phenotypes. Some reports have described phenotypes of activated T cells during the course of COVID-19 without assessment of bona fide antigen specificity, whereas other studies restricted phenotypic characterization to antigen-reactive T cells. Although such restriction to antigen-reactive T cells is clearly desired, it entails methodological challenges on its own: initial detection of antigen-reactive T cells usually requires in vitro re-stimulation with SARS-CoV-2 antigens. Upon re-stimulation, antigen-reactive cells can be defined through upregulation of activation markers (such as CD154) or release of effector cytokines (such as IFNγ). This, however, automatically also introduces major phenotypic biases for any downstream profiling since in vitro activated T cells show different phenotypes compared to unperturbed cells (i.e., cells as they are in vivo; technically, any analysis outside the body is ex vivo; we therefore here refer to unstimulated cells from our experiments as “ex vivo”; in contrast, we use the term “in vitro”, when cells are additionally re-stimulated since the stimulation step introduces major differences compared to the in vivo setting; finally, we use the term “in vivo” when the actual in vivo setting is referred to). In order to address these well-known challenges, peptide human leukocyte antigen (pHLA) multimers have been developed. Through removal of specifically designed pHLA multimers (“Streptamers”), unperturbed cellular phenotypes of antigen-reactive T cells can be even completely preserved. Yet, pHLA multimer technology requires a previous definition of specific epitopes and is restricted to individual HLA haplotypes. Furthermore, pHLA multimers are often difficult to generate for HLA class II-restricted CD4 T cells. These limitations represent a significant technical obstacle to investigating unbiased in vivo phenotypic profiles of antigen-reactive T cells.

Single-cell RNA sequencing (scRNA seq) allows simultaneous analysis of the global cellular transcriptome as well as identification of T cell receptor (TCR) sequences. Recently, it has been demonstrated that scRNA seq can be used to reveal activation-induced phenotypic profiles of antigen-reactive T cells. Samples can be split up after isolation from the tissue, stimulated in vitro in an antigen-specific manner (and, for comparison, left unstimulated), and then sequenced. The natural TCR can thereby serve as a barcode to link T cells of the activated and unstimulated condition belonging to the same in vivo expanded clonotype with a common antigen specificity.

Here, we show that such “reverse phenotyping” (Supplementary Fig. 1a) can be used to identify and characterize SARS-CoV-2-reactive T cells from PB of severely diseased COVID-19 patients. Furthermore, an integrated analysis of respiratory material from our own and independent reference cohorts shows that transcriptomic states of respiratory T cells from virus-positive patients are most similar to in vitro stimulated reactive T cells from PB, consistent with a “hot” phenotype driven by acute activation at the site of infection. Thus, we present transcriptional shifts from acute disease to resolution after virus clearance in antigen reactive CD4 and CD8 T cells during the course of COVID-19.

Results

Patient characteristics and experimental set-up for “reverse phenotyping”. We acquired respiratory material (TAs) as well as PB mononuclear cells (PBMCs) from severely diseased patients with COVID-19 (Fig. 1a; Supplementary Data 1). Consistent with the risk profile for severe disease, seven of nine patients in this “Munich cohort” were male and age ranged from 51 to 82 years (median 79 years). All patients were treated in an intensive care unit (ICU) and had been on a respirator for 8–38 days (median 29 days) at the time of sampling. After initial detection of SARS-CoV-2 via polymerase chain reaction (PCR), eight of nine patients had turned consistently virus-negative or had at least one prior negative test result at the time of sampling. Ultimately, two patients deceased and seven patients recovered. ScRNA seq (3’ transcriptomics) was performed on TAs from all nine patients. For two patients (“GT_3” and “GT_2”), we stimulated PBMCs with SARS-CoV-2 spike protein–peptide mix or left control samples unstimulated, and likewise performed scRNA seq (5’ transcriptomics and VDJ) after flow cytometry-assisted cell sorting of >10,000 CD4 and CD8 T cells for each patient.

Antigen-induced transcriptional shifts in PBMCs. After preprocessing, uniform manifold approximation and projection (UMAP) of stimulated and unstimulated T cells identified a group of cells in both patients which were separate from all other cells (Leiden cluster 29 in patient GT_3; Fig. 1b). The cluster encompassed both CD4 and CD8 cells and consisted almost exclusively of cells from the stimulated condition. We hypothesized that this distinct stimulation-induced cluster represented antigen-reactive T cells. Indeed, only the cells from that cluster upregulated IFNG (“the gene encoding Interferon-γ, IFNγ) after stimulation (Fig. 1c). Antigen-reactive CD4 Th cell lineages (particularly those that are not Th1 cells) do not necessarily express IFNγ in response to antigen. For this reason, and in order not to focus on upregulation of a single gene, we explored more holistic and unbiased antigen-reactive response scores for CD4 and CD8 T cells, as previously identified by scRNA seq after acBD3/acBD28 stimulation. Upon stimulation, CD4 T cells have been described to show sequentially enriched IFNγ response (early
Fig. 1 Single-cell RNA sequencing allows detection of transcriptional shifts induced by antigen-specific stimulation in TCR-barcode clonotypes. a Experimental setup; cells from tracheal aspirates and peripheral blood T cells (flow cytometry-sorted for CD4 or CD8 positivity) of intensive care unit (ICU) patients with COVID-19 were profiled by single-cell RNA sequencing (scRNA seq). Before scRNA seq, peripheral blood T cells were stimulated with SARS-CoV-2 spike protein–peptide mix or left untreated. b Uniform manifold approximation and projection (UMAP) of Leiden clusters (left panel), CD4 and CD8 T cells (middle panel), and stimulated and unstimulated T cells (right panel) (n = 11,460 cells in total). c IFNG expression, IFN response score, proliferation score, cytotoxic score, and cytokine score (from top to bottom) in unstimulated (left panels; stimulated cells shown in gray) or stimulated (right panels; unstimulated cells shown in gray) T cells (n = 11,460 cells in total). d Stimulated CD4 and CD8 T cells with highlighted pseudotime after defining the endpoint of pseudotime at the tip of cluster 29 (n = 11,460 cells in total). e IFNG expression in unstimulated or stimulated T cells for four representative clonotypes. For each clonotype, cells belonging to that clonotype are shown in an individual panel pair (cells from the unstimulated condition in left panels, cells from the stimulated condition in right panels), while cells not belonging to that clonotype are shown in gray (n = 11,460 cells in total, 43 cells for CD4 clonotype 19, 8 for CD4 clonotype 574, 61 for CD8 clonotype 244, 165 for CD8 clonotype 13). Data are shown for patient GT_3.
confirms previous observations of differential CD4 transcriptional responses through sensing of TCR-triggered cytokines such as IFNy\textsuperscript{18}. The source of the sensed cytokines could be antigen-reactive CD4 or CD8 T cells that are neighboring and stimulated in the culture system.

CD8 T cells have been described to undergo sequential transcriptional states upon activation that are reflected by high “cytotoxic” (early activation) or “cytokine secretion” scores (late activation)\textsuperscript{18}. While in our analysis almost all CD8 T cells showed a high cytotoxic score, high cytokine scores were exclusively confined to cells belonging to the antigen-reactive cluster 29 in the stimulated condition (Fig. 1c). Differential gene expression analysis confirmed that cluster 29 CD8 T cells showed upregulation of genes like IFNG, TNF, IL2, CCL3, CCL4, or GZMB (Supplementary Data 2 and 3), in line with CD8 T cell activation. We next aimed to elucidate if activation-induced transcriptomic changes followed consistent gradients. To this end, we defined the tip of cluster 29 as an “endpoint” in pseudo-time and ordered all stimulated cells along this trajectory of transcriptomic similarity (Fig. 1d). This shows that our approach could resolve a spectrum of activation states across clonotypes, feeding into cluster 29 from different directions. We validated our findings in the second severely ill patient (“GT_2”), for which we stimulated or did not stimulate PB CD4 and CD8 T cells with SARS-CoV-2 spike protein–peptide mix. Again, antigen-stimulation-induced transcriptional shifts giving rise to a specific “reactive Leiden cluster” (in this patient cluster 36; Supplementary Fig. 2a, b). Data integration showed that the reactive Leiden clusters from both patients showed convergent phenotypes (Supplementary Fig. 2c). The reactive clusters constituted 0.39% (cluster 36 in patient GT_2) or 2.88% (cluster 29 in patient GT_3) of all stimulated cells and were specific to the stimulated condition (Supplementary Fig. 2d).

Identification of antigen-reactive clonotypes. Using the TCR information from VDJ sequencing, we next investigated whether differential transcriptional responses to antigen stimulation could be attributed to specific clonotypes. We detected CDR3\textalpha sequences in 92% of analyzed T cells (69.9% fully paired CDR3\textalpha; 3.4% CDR3\textalpha only; 26.7% CDR3\textbeta only). In order to ensure the clonotypic nature of the investigated cells, we first only included clonotypes based on identical fully paired CDR3\textalpha sequences in our analysis. For both CD4 and CD8 T cell clonotypes, we recovered similar cell numbers in the stimulated and non-stimulated conditions (Supplementary Fig. 3a, c). This enabled us to identify clonotypes that underwent transcriptional shifts upon antigenic stimulation (Fig. 1e). Interestingly, we observed a heterogeneous response pattern within clonotypes, with some cells moving into the antigen-reactive cluster 29 (with concomitant upregulation of IFNG) and other cells staying in a transcriptional state that is consistent with their ex vivo phenotype without in vitro re-stimulation (Fig. 1e; Supplementary Fig. 3e). Possibly, these response patterns are a result of stochastic antigen encounters in the experimental stimulation system in vitro. The remarkable degree of transcriptional synchronization specific for each TCR ex vivo confirms previous observations of TCR-mediated phenotypic imprinting\textsuperscript{26,27} and renders high credibility to the assessment of clonotypes that are as small as a few cells per condition group (such as clonotype 574; Fig. 1e). Overall, the distinct transcriptional shifts induced by antigenic stimulation in specific clonotypes suggested the presence of antigen-reactive T cells.

While mean proliferation scores (for CD4 T cells) or mean cytokine scores (for CD8 T cells) generally correlated with mean IFNG expression per clonotype after antigen-specific stimulation (Supplementary Fig. 3b, d), IFNG expression seemed to be the more sensitive read-out. We, therefore, decided to define antigen-reactive T cells by significantly enhanced IFNG expression after antigen-specific stimulation (Fig. 2a, b). Among clonotypes with at least three cells in each stimulation condition, we detected five and four antigen-reactive clonotypes for CD8 and CD4 T cells, respectively. Apart from clonotype 574, reactive clonotypes were large in size, consistent with previous in vivo activation and clonal expansion.

This first analysis was strictly restricted to paired \(\alpha\beta\) TCRs. We also explored all clonotypes defined by unique double (CDR3\textalpha\textbeta) or single (CDR3\textalpha or CDR3\textbeta) chain sequences (Supplementary Fig. 4). This yielded two further CD8 clonotypes (clonotypes 651 and 548). Upon further examination, these single-chain (CDR3\textbeta only) clonotypes shared CDR3\textbeta sequences with clonotypes 81 and 244, respectively, and showed similar IFNG upregulation (Supplementary Fig. 4a) and global transcriptomic states ex vivo and upon stimulation (Supplementary Fig. 4b) compared to their paired partner clonotypes. We also identified an additional single-chain CD4 clonotype (clonotype 136), for which no paired partner clonotype existed (Supplementary Fig. 4c). These findings are best explained by the technical variability of CDR3\textalpha sequence detection. Since we conversely did not find any false-positive pairing of TCRs sharing the same CDR3\textbeta, but different CDR3\textalpha sequences, we included these single-chain clonotypes into downstream phenotypic analyses.

Having defined reactive clonotypes through statistically significant upregulation of IFNG after stimulation (based on a two-way ANOVA followed by Sidak’s multiple comparisons test), we aimed to ensure we would not miss clonotypes that show antigen-dependent reactivity through other means than IFNG upregulation. We therefore again analyzed cytokine/cytotoxicity scores for CD8 T cells and proliferation/IFN response scores for CD4 T cells in a clonotype-dependent manner. While for CD8 T cells, no clonotype-dependent enrichment was visible after stimulation in the cytotoxicity score (early activation), in the cytokine scores (late activation) we detected broad statistically significant signals, which did not mirror global transcriptomic shifts in sanity checks and therefore seemed to reflect rather unspecific changes (e.g., compare statistically significant results for clonotype 13 in Supplementary Fig. 4a with missing reactivity in Fig. 1e). In CD4 T cells, clonotype and stimulation-dependent IFN responses (early activation) likewise yielded inconsistent results (Supplementary Fig. 4c), whereas the proliferation score (late activation) identified the same antigen-reactive clonotypes as defined through IFNG upregulation except for one clonotype, which was missed by the proliferation score (Supplementary Fig. 4c). Finally, targeted exploration of markers alternative to IFNG, such as MKI67, TNFRSF9 (coding for CD137), IL-2, IL-4, IL-5, IL-9, IL-10, IL-13, IL-17, or IL-22 did not yield any statistically significant antigen-induced upregulation in a clonotype-dependent manner.

To capture the global antigen-specific reactivity landscape of the TCR repertoire, we calculated correlations between clonotypes in terms of the general transcriptomic shift these clonotypes underwent upon stimulation. This revealed two groups of clonotypes that showed high inter-clonotype correlations within the respective group (Supplementary Fig. 5a). The larger group consisted mostly of CD8 clonotypes assessed as non-reactive to antigen based on the lack of statistically significant IFNG upregulation and recruitment into cluster 29. The few clonotypes that are antigen-reactive and/or belong to cluster 29 in that larger group may represent weakly cross-reactive clonotypes. A smaller group contained almost exclusively CD4 and CD8 clonotypes that we defined as antigen-reactive based on statistically significant IFNG upregulation (Supplementary Fig. 4) and/or were present in the stimulation-induced cluster 29 (Fig. 1b).
In order to experimentally validate the antigen reactivity of our selected clonotypes, we generated TCR-transgenic T cells by CRISPR/Cas9-mediated orthotopic TCR replacement (OTR) [28]. Through this technology, transgenic TCRs are knocked into the endogenous TCR gene locus, thereby simultaneously placing the transgenic TCR under physiological transcriptional control and knocking out the endogenous TCR. We equipped healthy donor T cells by OTR with identified CD4 TCRs (Fig. 2c). From our screening of clonotypes with at least three cells in each condition (Fig. 2b), we included the four TCRs defined as reactive (TCRs 138, 19, 256, and 574) and the TCR from the largest CD4 clonotype (TCR 48), which did not show antigen-induced transcriptional changes. After TCR knock-in (KI), T cells with TCRs that were previously defined as reactive (TCRs 138, 19, 256, and 574) all showed SARS-CoV-2 spike antigen-dependent reactivity, whereas TCR 48 KI T cells did not (Fig. 2d, e). To test the sensitivity of our system, we additionally investigated TCRs from two very small clonotypes (1373 and 1904), which were not included in the initial definition of reactive clonotypes (Fig. 2b) since they had less than three cells in each condition. Remarkably, we could validate reactivity for TCR 1904, which had a transcriptional shift into cluster 29 with concomitant IFNG upregulation in one of two cells in the stimulated condition, whereas reactivity for TCR 1373 was missing, as predicted based on the lack of IFNG upregulation and no movement into cluster 29 (Fig. 2e, Supplementary Fig. 5b). Overall, these data reinforced our approach to using stimulation-induced IFNG upregulation as a surrogate marker to detect antigen-reactive clonotypes and functionally validated SARS-CoV-2 reactive TCRs.

Reverse phenotyping reveals in vitro antigen re-stimulation-induced phenotypic biases in PB T cells. The identification of antigen-reactive clonotypes enabled us to perform “reverse phenotyping” by “looking back” at the phenotype without re-stimulation for clonotypes that undergo defined functional changes after re-stimulation, using their TCR sequence as natural barcodes. In other words, this enabled us to define antigen-reactive clonotypes by a functional read-out, and then investigate the phenotype of these cells at the phenotype without re-stimulation. Through this, we can on the one hand investigate systematic phenotypic effects that are introduced by antigenic re-

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Fig. 2 Identification and validation of SARS-CoV-2 antigen-reactive T cell receptors. a Top: IFNG expression of CD8 clonotypes after antigenic or no stimulation. Only clonotypes with at least three cells in each condition and as defined by a unique αβ CDR3 sequence were included in this analysis. Each dot represents one cell and lines indicate the median. n = 56/66 (clone 81), 38/30 (clone 304), 25/30 (clone 244), 16/16 (clone 152), and 23/22 (clone 104) cells for stim/unstim condition, respectively. Exact cell numbers per clonotype can be found in Supplementary Data 11. Antigen-reactive clonotypes (defined through statistically significant upregulation of IFNG) are highlighted, p < 0.0001 for clones 81, 244, and 104; p = 0.0033 for clone 304. Bottom: Clonotype sizes in numbers of total cells analyzed. Clonotypes de

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stimulation in vitro, and on the other hand, explore the unper- 
turbed ex vivo phenotype of antigen-reactive T cells.

Upon re-stimulation in vitro, antigen-reactive CD4 T cells 
upregulated TNFRSF9 (encoding CD137) and effector cytokines: IFNG, TNF, XCL1, XCL2, or CCL3 were absent in unstimulated reactive CD4 T cells, but strongly induced upon stimulation (Fig. 3a, Supplementary Fig. 6a). GZMB or CCL4 were expressed in reactive CD4 T cells (as well as in non-reactive cells) in the unstimulated condition already, but the expression was boosted by stimulation for reactive CD4 T cells only (Fig. 3a). Of note, co-inhibitory molecules, such as PD-1 (PDCD1), LAG3, or TIGIT, were almost absent on antigen-reactive cells before stimulation, and only induced thereafter, indicating that detection of these molecules in in vitro stimulated T cells reflects T cell activation rather than exhaustion.

Indeed, many induced molecules are known to be differentially regulated after antigen stimulation but also serve as important determinants of more stably committed T cell phenotypes. High expression of ICOS, PDCD1, and TIGIT has previously been described as a hallmark of SARS-CoV-2 specific CD4 T cells during severe disease, but our findings indicate that the degree of expression can be significantly overestimated due to confounding stimulation effects. Conversely, expression of CXCR4 or KLRB1 would have been underestimated if cells had only been assessed after stimulation. CXCR4 is known to be more expressed in less differentiated T cells but downregulated upon T cell activation. We next wondered whether and how in vitro stimulation with antigen also changed Th lineage-defining transcription factors, since these are particularly relevant for the assignment of CD4 T cell identity. Despite their robust IFNG upregulation upon antigenic stimulation, reactive CD4 T cells showed overall less Th1-defining TRX21 (T-bet) expression ex vivo than it would have seemed after stimulation (Fig. 3a). Vice versa, expression of EOMES and Th2-defining GATA3 was downregulated in reactive CD4 cells after antigenic stimulation (Fig. 3a). Antigen stimulation also induced expression of (circulating) follicular helper T cell ((c)Tfh)-defining BCL6 in a “false-positive” manner in a few antigen-reactive CD4. Overall, we revealed that stimulation-induced broad changes in transcriptional profiles, ranging from expected upregulation of activation markers to more unexpected and complex changes in markers associated with stable phenotypes.

The mentioned observations account for comparisons of stimulated vs. unstimulated and reactive vs. non-reactive clonotypes in bulk (Fig. 3a). However, individual clonotypes have also different phenotypes a priori, and could therefore show unique reactivity upon stimulation. To explore this further, we analyzed stimulation-induced transcriptional changes for individual reactive clonotypes. This revealed expected as well as unexpected, consistent as well as heterogeneous phenotypic
changes for reactive clonotypes. For example, while all reactive clonotypes upregulated *PDCD1* or downregulated *CXCR4* upon stimulation in a synchronized manner, stimulation-induced clonotype-specific changes in CD4 lineage defining *TBX21* and *GATA3* (Fig. 3b). Clonotype 138 upregulated and clonotype 256 downregulated *TBX21* expression after stimulation. In addition to this inter-clonal heterogeneity, intra-clonal variability adds an additional layer of complexity (Fig. 3b) since individual clonotypes can show mixed phenotypes. Indeed, all reactive CD4 clonotypes contain cells that express *TBX21* and/or *GATA3*. We could however not detect a statistical dependency between *TBX21* and *GATA3* expression (see "Methods" section), suggesting that their expression is independent or that correlation could not be resolved.

Reactive CD8 T cells were overall less affected by antigenic stimulation than reactive CD4 T cells. After stimulation, CD8 T cells upregulated *IFNG* or *CCL4*, and also appeared more *LAG3* or *PDCD1* expressing than they were ex vivo (Supplementary Fig. 6b). In previous studies, these latter molecules have been described to be strongly increased in SARS-CoV-2 specific CD8 T cells during severe disease, providing further evidence that phenotypes of T cells after in vitro re-stimulation with antigen should be interpreted with caution.

To further characterize the stimulation-induced changes of antigen-reactive CD4 and CD8 clonotypes, we performed differential expression analysis (Supplementary Fig. 6c, d; Supplementary Data 4 and 5). In CD4 T cells, this confirmed stimulation-induced upregulation of genes associated with induction of T cell activation,32-35 or downregulation of genes known to be associated with repression of T cell activation,35-37 but also revealed more unexpected differential gene expression of the Treg maker *FTHD*, or of *TMSB4X* which is associated with effector-like Th1 cells. In CD8 T cells, stimulation induced *GZMB* or *PRF1* most strongly, but was also associated with a prominent signature of actin (-binding) genes, which has previously described effector rather than exhausted T cells.32

In summary, reverse phenotyping unraveled expected and unexpected phenotypic effects introduced by antigenic re-stimulation in vitro. The results thereby also highlight transcriptional differences between currently and previously activated T cells. Beneath the surface of global transcriptomic shifts on the population level, single-cell resolution together with TCR barcoding demonstrates additional inter- and intra-clonal heterogeneity.

**Unperturbed ex vivo phenotypes of SARS-CoV-2-reactive T cells in PB.** After comparing the differences between stimulated and unstimulated reactive clonotypes, we next focused on the unperturbed ex vivo phenotypes of SARS-CoV-2-reactive T cells in further detail by comparing them with unreactive clonotypes in the unstimulated condition only. Reactive CD4 T cells selectively stemmed from a T cell effector memory (TEM) Th1-like group of cells, which was transcriptionally similar to CD8 T cells (Fig. 3c, Supplementary Fig. 7a-d). Two CD4 clusters (CD4 clusters 2 and 7) entailed Th1 cells. Both clusters were the only ones harboring expanded clonotypes (Supplementary Fig. 7e), were high in *IL7R* and *CXCR4*, but low in *CCR7* and *CD27*, and were the only clusters that expressed *CXC3CR1*, speaking for a TEM-like phenotype. Remarkably, reactive CD4 clonotypes were exclusively found in CD4 cluster 2, but not in cluster 7. Cluster 7 consisted of cells belonging to a single clonotype (number 48, the largest clonotype found for CD4 T cells; Fig. 2b). The similar phenotype, but lacking reactivity of this clonotype could indicate that clonotype 48 recognizes an entirely different target or a different part of SARS-CoV-2 (non-spike).

Reactive CD8 T cells were more evenly distributed across different CD8 TEM-like Leiden clusters (Fig. 3c, Supplementary Fig. 7). Of note, most CD8 T cells and the CD4 Th1 clusters showed clonal expansion, whereas few CD8 T cells and all non-Th1 CD4 clusters were clonotypically highly diverse (Fig. 3c), consistent with their overall little differentiated IL7R+ CCR7+ phenotype (Supplementary Fig. 7f).

To precisely define the ex vivo phenotypes of SARS-CoV-2-reactive T cells in an unbiased manner, we performed differential gene expression analysis comparing reactive and non-reactive clonotypes in the unstimulated condition (Supplementary Data 6 and 7). This identified *KLRB1* to be most significantly upregulated in reactive CD4 T cells (Fig. 3d). *KLRB1* encodes C1D1 and is part of cytotoxic/Th1 anti-viral T cells.45 It has also already been described to be upregulated in SARS-CoV-2 reactive T cells after antigenic re-stimulation in vitro. Together with *IL7R* expression, *KLRB1* also marks MAIT cells, but the TRAV/TRAJ expression of our antigen-reactive TCrs did not reflect invariant chains expressed by MAIT cells.27

Antigen-reactive CD8 T cells were characterized by high expression of granymes, *CCL5* or the cytotoxic marker *NKG7*, as well as CD52, the target of Alemtuzumab, for which a paracrine suppressive function is described in activated CD4 T cells (Fig. 4d, Supplementary Fig. 8a). Reactive antigen-reactive CD8 T cells also were markedly lower in *TYROBP*, *KIR2DL3*, and *KLRD3*. *TYROBP* encodes DAP12 and has known activating as well as inhibitory immune cell signaling roles when pairing with receptors belonging to the killer inhibitory receptors (KIR) or killer lectin-like receptor (KLR) family.45 In CD8 T cells, *TYROBP* and KLR transcripts have previously been shown to be downregulated after activation.46

Using these differentially expressed genes of reactive and non-reactive cells in the unstimulated condition, we defined transcriptional signature scores characteristic for antigen-reactive CD4 or CD8 T cells ex vivo. These “ex vivo signature scores” overlapped to some extent with “stimulation-biased signature scores” that we defined by using differentially expressed genes of reactive and non-reactive cells in the stimulated condition (Supplementary Data 8 and 9), but also showed differences (Supplementary Fig. 8a-f). For example, for CD8 cells, *GZMB* upregulation is only part of the “stimulation-biased signature score”, *GZMHI* upregulation is part of both scores, and *GZMA* and *GZMM* upregulation is only part of the “ex vivo signature score”. We cross-validated the “ex vivo signature” and “stimulation-biased signature” scores generated based on data from patient GT_3 in patient GT_2 and achieved high linear separability for both scores (Supplementary Fig. 8g, h).

Overall, we could precisely identify the phenotypes of currently and previously activated antigen-reactive PB T cells.

**Matching phenotypes of PB antigen-reactive T cells and the respiratory tract of COVID-19 patients.** We next wondered whether we could identify T cells with our antigen-reactive transcriptional signatures in the respiratory tract. Tracheal aspirate (TA) T cells from identical as well as eight additional patients clustered in-between stimulated and unstimulated reactive clonotypes from PB (Supplementary Fig. 9a). TA CD8 T cells showed *IFNG* expression and high cytokine scores, whereas for CD4 T cells neither *IFNG* nor high proliferation scores were detectable (Supplementary Fig. 9b). These results were further corroborated by gene expression analyses of TA T cell clusters (Supplementary Fig. 10). Notably, TA CD4 T cells did not express...
ZNF683, encoding the Tissue-resident memory (TRM) T cell-associated transcription factor Hobit, and expressed little ITGA1, encoding the TRM marker CD49a. TA CD8 T cells, in contrast, expressed ZNF683 and ITGA1 throughout. While these TRM markers differentiated them from antigen-reactive PB CD8 T cells, TA CD8 T cells were overall very similar to reactive PB T cells—especially from the stimulated condition—with high expression of IFNG, PDCD1, or CD38 (Supplementary Fig. 10). These data indicated that particularly CD8 T cells from the respiratory tract of COVID-19 patients showed a phenotype that is similar to in vitro activated antigen-reactive CD8 T cells from PB.

To further test this hypothesis and investigate whether this was a feature that is specific for severe disease states, we integrated previously published and publicly available scRNA seq data sets from the respiratory tract of COVID-19 patients with severe disease, mild disease, and healthy controls, from Berlin17, Shenzhen48, and Chicago49 in addition to our own Munich cohort (see “Methods” for further information on data set integration). In total, we analyzed 279,663 cells from 50 patients (including 30,033 T cells from 28 patients; Supplementary Fig. 12b). Leiden cluster 29 T cells (Fig. 1b) were also enriched in this area (Fig. 4a). We next analyzed the relative distribution of each cell type across Louvain clusters (Fig. 4b). Louvain cluster 11 was enriched for respiratory T cells from severely diseased patients and was at the same time the cluster that encompassed the most reactive PB clonotypes from the stimulation condition (Supplementary Fig. 12b–f). Louvain cluster 11 was enriched for CD8 and CD4 respiratory T cells from severely diseased patients and at the same time the cluster that encompassed the most reactive PB clonotypes from the stimulation condition (Supplementary Fig. 12b–f). Leiden cluster 29 T cells (Fig. 1b) were also enriched in this area (Fig. 4a). We next analyzed the relative distribution of each cell type across Louvain clusters (Fig. 4b). Hierarchical clustering confirmed the high proximity of respiratory CD8 T cell states to reactive PB CD4 and CD8 T cells from the stimulated condition, which were highly enriched in Louvain cluster 11. Intriguingly, PB CD8 reactive T cells clustered together with respiratory CD8 T cells from severely diseased patients particularly from Chicago and Shenzhen, which in contrast to the Berlin cohort encompassed a substantial number of virus-positive patients very early after entering the ICU. We, therefore, hypothesized that the phenotypic signatures of our stimulated or unperturbed reactive clonotypes could reflect, respectively, “hot” (active virus replication) or “cold” (virus cleared) respiratory tract environments of severely diseased patients, in which, respectively, virus was still detectable or not detectable anymore.

Based on the dominance of stimulated or unperturbed CD4 or CD8 clonotypes, we predicted Louvain clusters to be hot or cold CD4 or CD8 clusters, with cluster 11 being a generally “hot” T cell cluster and for example, the areas around clusters 5 and 13 reflecting “cold” CD4 and CD8 environments, respectively (Fig. 4a, b). We then analyzed how many respiratory CD4 or CD8 T cells were present in those clusters. Unperturbed T cell signatures of reactive clonotypes were associated with “cold” respiratory environments from severely diseased, but virus-negative patients. In contrast, stimulation-induced T cell signatures of reactive clonotypes were associated with “hot” respiratory environments from severely diseased, virus-positive patients, as most prominently visible for Louvain cluster 11 (Fig. 4c). As an individual gene, CCL4 was markedly upregulated in respiratory T cells from patients with severe disease, and even more so in virus-positive patients. This is reflected by higher expression in reactive T cells from PB, with particularly pronounced expression in the stimulated condition (see also Supplementary Fig. 8).

Overall, these data indicate that ex vivo stimulation induced a transcriptional state in antigen-reactive T cells from PB which is highly similar to T cells found in the respiratory tract from severely diseased patients with high viral loads (“hot” environments). In contrast, respiratory T cells from severely diseased patients in which no virus is detectable anymore (“cold” environments) showed a phenotype that is similar to PB antigen-reactive T cells when they are not additionally re-stimulated ex vivo. We could thereby interrogate connections between disease stages of individual patients and phenotypic signatures of respiratory T cells, for which currently and previously activated PB T cell subsets provided a framework.

Modeling intercellular communication between respiratory T cells with antigen-reactive signatures and SARS-CoV-2-positive macrophages. We finally aimed to test how the definition of transcriptional signatures from antigen-reactive T cells after different antigen stimulation conditions can be leveraged across publicly available scRNA seq data sets. To this end, we investigated the intercellular communication between macrophages and respiratory T cells that bear our antigen-reactive signatures. We used scRNA seq data from the “Chicago cohort”49, for which a macrophage-T cell circuit has been described. The samples in this cohort of severely diseased patients were acquired 48 h after intubation when the virus was still detectable via scRNA seq. Macrophages in which SARS-CoV-2 transcript was detectable (either after direct infection or after phagocytosis of infected cells) seemed to sense IFNγ produced by T cells and in turn, released T cell-targeting cytokines49. These macrophages included tissue-resident alveolar macrophages (TRAM) as well as monocyte-derived alveolar macrophages (MoAM). To study the cross-talk between these macrophages and T cells with our antigen-reactive signatures systematically, we applied NicheNet (see “Methods”). The NicheNet algorithm ranks ligands expressed by “sender” cells according to their ability to induce a set of target genes in “receiver” cells. Thereby, the algorithm exploits the transcriptomic signatures of receiver cells, building on prior knowledge on gene regulatory networks from public databases beyond the mere expression of matching ligands and receptors by sender and receiver cells, respectively50.

We first investigated which T cell ligands are predicted to induce the differentially expressed genes between SARS-CoV-2 transcript positive and negative macrophages. Compared to SARS-CoV-2-negative TRAM1, SARS-CoV-2-positive TRAM2 highly expressed cytokines such as CCL2, CCL3, CCL4, CXCL9, CXCL10, and CXCL11, as well as molecules that have previously been described to play a role in chemotaxis (e.g., ICAM1) and responsiveness to IFNγ (e.g., STAT1) in the interplay between monocytes and T cells during COVID-1947 (Supplementary Fig. 13). IFNG and TNF were predicted to be the most important ligands expressed by T cells that could induce the transcriptomic
changes observed between SARS-CoV-2 transcript positive and negative TRAM. In T cells, the ligands IFNG and TNF were most dominantly expressed in Louvain cluster 11, which also highly expressed the predicted ligands CCL3 and CCL4 (Supplementary Fig. 13). The prediction pattern of the additional top-predicted ligands also coincided with the other hot or cold Louvain cluster (Fig. 13). The prediction pattern of the additional top-predicted ligand (Fig. 4b) stood out through their high expression of the predicted signature in a specific manner. To reflect the “hot” environment of the investigated patients in which the virus was still present, we utilized NicheNet to predict which ligands and disease stages.

We next wondered whether SARS-CoV-2 transcript carrying macrophages would also signal back to T cells with our antigen-reactive signature in a specific manner. To reflect the “hot” environment of the investigated patients in which the virus was still present, we utilized NicheNet to predict which ligands expressed by Macrophages could induce the genes distinguishing reactive from unreactive T cells from the stimulated condition in CD4 and CD8 T cells. The definition of these target gene sets,
including GZMB, IFNG, TNF, CCL3, and CCL4 in stimulated reactive CD4 T cells, led to the prediction of macrophage-derived co-stimulatory ligands such as IL-15, IL-18, CCL4, CCL8, or CXCL9, which have been described to be upregulated in macrophages from the respiratory tract during COVID-19 also in the original studies on the Berlin and Shenzhen cohorts27,28 (Supplementary Fig. 15). For CD8 T cells as receivers, NichiNet predicted macrophage-derived co-stimulatory ligands CCL2 and SPP1 (which encodes Osteopontin27,28) to drive CCL4 and CCL3 expression, as well as IL-15, IL-18, ICAM1, ADAM17, CD80, and CD86 to drive IFNG, TNF, and GZMB expression (Supplementary Fig. 16). Intriguingly, most of the ligands that were predicted on the basis of target genes from our antigen-reactive CD4 and CD8 T cell signatures were preferentially expressed by the very macrophage subtypes in which SARS-CoV-2 transcript was detectable (TRAM2 and Moma1). Overall, these data indicate a specific ligand-receptor cross-talk between respiratory T cells with antigen-reactive signatures and SARS-CoV-2-positive macrophages.

Discussion

We here show how barcoding through natural TCR sequences can be used to identify SARS-CoV-2 antigen-reactive T cells after differential stimulation with and without antigen, followed by scRNA seq. Antigen-reactive clonotypes showed consistent transcriptomic shifts upon stimulation, as visible by induction of a distinct cluster in a UMAP projection, expression of generic T cell activation scores along continuous pseudotemporal gradients, and high degrees of inter-correlative gene expression changes. As a single marker, IFNG upregulation proved to reliably identify SARS-CoV-2 antigen-reactive CD4 and CD8 T cells. We validated reactive TCRs by transgenic re-expression using CRISPR/Cas9-mediated OTR. Such SARS-CoV-2 reactive TCR-transgenic T cells serve as a potential resource for future immunotherapy of COVID-19 infection. Furthermore, the presented approach represents a generic platform for the identification of antigen-reactive TCRs for a plethora of a priori phenotypically heterogeneous clonotypes at once.

In addition to the identification of antigen-reactive clonotypes per se, “reverse phenotyping” allowed us to investigate the phenotypic profile of antigen-reactive T cells with or without antigenic re-stimulation. This revealed systematic biases induced through re-stimulation and allowed exploration of unperturbed T cell states. By profiling antigen-stimulated CD4 T cells from PB via scRNA seq, it has recently been shown that SARS-CoV-2 antigen-reactive CD4 T cells—particularly in patients with severe disease—show a particularly pronounced cytotoxic profile10,14,16 compared to CD4 T cells specific for other viruses15. We confirm these findings by demonstrating that CD4 T cells which show major transcriptional shifts upon antigenic stimulation robustly upregulate IFNG. However, our “reverse phenotyping” approach also reveals that the classical Th1-ness (as defined by TBX21 expression) of those cells is overestimated after stimulation, and that—in vivo—antigen-reactive PB T cells instead show signatures that are far more dominated by EOMES and GATA3 than it appears after stimulation. The role of EOMES in CD4 T cells is less clear compared to other Th lineage defining core transcription factors, but recent evidence suggests that EOMES drives a cytotoxic signature and represses Th17 features33,34. Apart from Th1-polarized CD4 cells, antigen-reactive cT cells have been reported by several studies5. In our patient subset with a severe disease course, we observed BCL6 and ICOS expression in antigen-reactive CD4 clonotypes upon stimulation only. While this does not exclude the possibility that cT cells plays a dominant role in the adaptive immune response to SARS-CoV-2, these findings provide examples of the phenotypic biases introduced by antigen stimulation prior to phenotyping.

Both CD4 and CD8 antigen-reactive T cells showed TEM/T cell effector phenotypes with less expression of co-inhibitory molecules and markers of terminal differentiation than would be expected based on the phenotypes after stimulation. However, at the same time, antigen-reactive CD4 and CD8 T cells were characterized by a more cytotoxic and differentiated profile in comparison to antigen-unreactive T cells when stimulation biases are accounted for. Thereby, reverse phenotyping allowed us to define more accurately the actual ex vivo phenotypic profiles of SARS-CoV-2 antigen-reactive T cells. We performed reverse phenotyping on T cells only from PB, in a limited number of patients with severe disease, and focused on T cell reactivity to virus spike antigens. More comprehensive experimental analyses of SARS-CoV-2 antigen-reactive T cells are needed—including different time points and disease severities—to more comprehensively map the ex vivo phenotypic profile of SARS-CoV-2 specific T cells. Also, investigation of additional antigen groups (including the whole SARS-CoV-2 proteome) and specific epitopes (to also account for potential underrepresentation in the 15mer peptide mix that was used for this study) will be of importance for future studies, explicitly including antigenic changes as present in SARS-CoV-2 variants of concern. Here, we provide proof of concept that “reverse phenotyping” can be used for that purpose.

Publicly available data sets—particularly those that are bundled in a coherent manner as within the Human Cell Atlas initiative—represent a vast resource of deeply profiled immune cells from many different patients and disease contexts. However, in these data sets often no dedicated antigen-specific T cell analyses have been performed. In T cells from the respiratory system of identical as well as further patients—including patients from independent reference cohorts—we detected transcriptional signatures that overlapped with those we defined based on antigen-reactive T cells from PB. In vitro stimulated reactive T cells thereby mirrored “hot” cell states from virus-positive patients with severe disease, whereas unperturbed T cell states reflected “cold” cell states from virus-negative patients with severe and mild disease. Interaction of T cells with viral antigens at the site of infection could explain these findings. In the future, it will be exciting to further investigate the role of SARS-CoV-2 antigen-reactive T cells at the site of infection as well as in PB, e.g., by using TCR sequences to precisely define ontogenic relationships.

As a tool for T cell immunology, scRNA seq after differential antigen stimulation opens up avenues for the identification and characterization of antigen-reactive T cells by exposing gradients of antigen reactivity and reverse phenotyping. It thereby contributes to a deep understanding of the adaptive immunity induced by a viral infection, which will be pivotal to guide the enhanced and accelerated development of therapies and vaccines for emerging pathogens such as SARS-CoV-2.

Methods

Munich cohort patients

Clinical information and material. All Munich cohort patients were PCR-confirmed SARS-CoV-2 positive, admitted to the ICU in the University Hospital of the Ludwig-Maximillian’s University, Munich (n = 5), or the Asklepios Lung Clinic Munich-Gauting, Gauting (n = 4), for treatment of severe COVID-19 requiring invasive, mechanical ventilation. For further clinical information see Supplementary Data 1. PBMCs and TA samples were taken at the end of April 2020.

Consent. Written informed consent was obtained from the donors or their caregivers, usage of the blood samples was approved according to national law by the local Institutional Review Board (Ethikkommission der Medizinischen Fakultät der Ludwig-Maximilian-Universität München; vote IDs 19-629, 19-630, and 20-259) and/or samples were used according to legal provisions defined by the German Infection Protection Act (IfSG).
T cells from PBMCs

Cell culture. PBMCs were isolated from EDTA whole blood by gradient density centrifugation according to the manufacturer's instructions (Biochrom, Biochrom) and frozen in FCS + 10% DMSO (Merck) for liquid nitrogen storage. After freezing–thawing procedure, T cells were cultured in RPMI 1640 (Gibco) supplemented with 5% human serum, 0.025% l-glutamine, 0.1% HEPES, 0.001% gentamicin, and 0.002% streptomycin (hereafter RPMI-HS).

Antigen-specific stimulation and flow cytometry-assisted cell sorting prior to scRNA seq. PBMCs were stimulated with 0.6 nM of SARS-CoV-2 spike protein–peptide mix (PepTivator® SARS-CoV-2 Prot_S, Milltenyi). For the unstimulated condition, PBMCs were only cultured in RPMI-HS. After stimulation for 4 h at 37 °C, surface staining was conducted for 20 min with the following fluorochrome-conjugated antibodies: CD3-APC (1:200), CD4-PE (1:100), CD56-FITC (1:100), CD8-Fluor450 (1:200) (Life Technologies, 17-0038-42, 48-0086-42,) and CD19-ECD (1:100) (Beckman Coulter, A07770). Propidium iodide (Invitrogen) was used for live/dead discrimination. Flow sorting of CD4+ and CD8+ cells from the stimulated and unstimulated condition was conducted on a MoFlo Astrios EQ (Beckman Coulter) under biosafety level 3. For a representative gating strategy, see Supplementary Fig. 17a.

TCR DNA template design and CRISPR–Cas9 mediated TCR KI. DNA constructs for CRISPR-Cas9-mediated HDR at TRAC target were designed in silico with the following structure: 3' homology arm (300–400 base pairs (bp)), P2A, TCR-β (including the TCR CDR3), additional cytomegalovirus (CMV) promoter (T2A), TCA–tcR–c (180–200 bp) and additional cytosine bridge, SGHpaI tail, 3' homology arm (300–400 bp). All TCR DNA template sequences were synthesized by Twist Bioscience. CRISPR-Cas9-mediated TCR KI and KI were performed as previously described on isolated PBMCs from donor whole blood. In short, bulk PBMCs were activated on anti-CD3/anti-CD28 coated plates (20,000 reads/cell) for 10–12 h in RPMI supplemented with 180 IU/ml IL-2 until a marginal frequency of 0.5 was observed. This protocol (Chromium Next GEM Single Cell VDJ Kits v3.1).

Single-cell RNA sequencing data analysis

Data processing. After sequencing, the processing of next-generation sequencing reads of the scRNA-seq data was performed using CellRanger version 3.1.0 (10x Genomics) with a customized reference genome. To account for transcripts originating from the virus, the genes of the SARS-CoV-2 genome (NCBI Reference Sequence: NC_045512.2) were manually added to the hg38 (GRCh38.99) human reference genome’s GTF files. Negative strands of the viral genes were additionally added. The genome was indexed via CellRanger’s “mkref” command.

Initial unsupervised analysis of PB T cells. We performed unsupervised analysis for multiple subsets of the data with scapy56 (v1.6.0): Both patients, patient GT_3 only, patient GT_2 only, stimulated or unstimulated condition only for both patient GT_3 and GT_2, separately. In all cases, we first filtered genes that were expressed in at least 10 cells, scaled cell-wise expression vectors to a total count of 10,000, and log1p-transformed the data and selected highly variable genes (flavor = “seurat”). We then performed a principal component analysis, computing 50 components, based on which we computed a k-nearest neighbor graph (k = 50). We then computed UMAPs57 and Leiden or Louvain clusterings58. The complete code for this analysis is reported in the Source Data file.

Cell type assignment of PB T cells. CD4 and CD8 expressing cells did not clearly separate in Leiden groups. Therefore, we chose a two-staged cell type assignment process: First, we assigned Leiden groups to either CD4+ or CD8+ T cells based on their relative mean expression in the group. Secondly, we re-assigned cells from clonotype analysis (see also: Clonotype analysis), which contained both putative CD4+ and CD8+ T cells, to the major cell type found in this clonotype.

Cell state assignment of PB T cells. We re-clustered CD4 and CD8 cells in the unstimulated condition separately using the Leiden algorithm to identify cellular states at a higher resolution than cell types. For this purpose, we repeated the unsupervised analysis as described above on this subset of cells. Throughout the manuscript, these clusters are ordered by similarity in heatmaps and dot plots. This ordering is derived from a hierarchical clustering based on all genes with mean expression larger than 0.5 in the selected subset.

Clonotype assignment of PB T cells. We performed TCR scRNA sequence analysis with scirpy59 (v0.4). We de

Pseudotime analysis of PB T cells. We computed pseudotime-based scores by computing diffusion pseudotime49 with respect to a cell in the reactive T cell cluster in patient GT_3. This root T cell was selected based on its extremal position in the UMAP, at the tip of the reactive cluster. The nearest-neighbor graph underlying the pseudotime computation was derived as described in section initial unsupervised analysis. The complete code for this analysis is reported in the Source Data file.

Differential expression analysis of PB T cells. We performed differential expression analysis with dffpx (v0.7.4). We used Welch’s t test on log-normalized UMIs to compare expression differences between two groups of cells. We labeled genes as differentially expressed if they had a Benjamini–Hochberg corrected p value of less than 0.01 and a mean expression of at least 0.5.
Tissue residency score of PB T cells. We computed expression z-scores for the following genes associated with tissue residency46: CA10, CRTAM, CXCR1, CXCR3, CXCL9, CXCL10, CXCL11, IL10, IL22, IFGTL1, ITGAE, KCNK5, KL2F, KL3F, KRT72, KRT73, NPDCI, PDCD1, PTGDS, RAPTAG2, RGSI, SIRP1, SREK1, SELL, SOX13, STX38, TSPAN18, TTC16, and TTYH2. We aggregated these cell- and gene-wise z-scores to a cell-wise tissue residency score by taking the mean across all gene-wise z-scores.

Unsupervised analysis of TA data. The count matrices output by CellRanger were again analyzed using Scanypy (v.1.6.0). For barcode filtering, we excluded barcodes with less than 200 detected genes. A high proportion (>10%) of transcript counts derived from mitochondria-encoded genes may indicate low cell quality, and were therefore removed in the downstream analysis. The number of unique molecular identifiers (UMIs) was explored via patient-wise violin plots, and individual upper cut-offs were applied ranging from 5000 to 8000 UMI counts. Genes were only considered if they were expressed in at least three cells in the data set. As we observed a certain degree of ambient RNA bias, we applied SoupX version 1.3.66 to lessen this effect with mostly default parameters, setting the contamination fraction manually to 0.3.

The expression matrix was normalized using scan’s normalization approach43, in which size factors are calculated and used to scale the counts in each cell. The data were then log1p-transformed and the top 4000 variable genes were selected for each patient individually (flavor="seurat"). Genes that were listed as a variable in at least 10% of patients (1584 genes after removing cell cycle genes) were used as basis for the principal component analysis. BBKNNn was employed to construct a batch-corrected neighborhood graph using the first 20 components and individual patient labels as batch keys. Unsupervised clustering was performed with Louvain at resolution three and was manually annotated based on the manual exploration of known marker genes. As T cell subtypes were of particular interest, we subdivided the data set to CD3E high cluster and refined the annotation after re-clustering and assessing of mean expression of CD8A, CD8B, and CD4 in the respective cluster.

Computational data integration

Computational data integration—Munich TA and PBMC. In contrast to the results from the PBMC data set with very 10X patient samples, the number of log1p-transformed matrices of both objects after initial filtering were concatenated. The variable gene selection was performed anew with more stringent parameters on this combined object. The top 800 genes (flavor="cell_ranger") were selected for both data sets separately, resulting in 183 variable genes labeled as such in both calculations. Principal component analysis (PCA) and the neighborhood graph were re-calculated using 50 components and 15 neighbors. The cell type annotation established on the separate objects was retained.

Computational data integration—includes recent Covid-19 related BALF data sets. To test the generalizability of our results on independent cohorts and in order to include various known viral, inflammatory, and healthy control data in our analysis, we combined our single-cell data (Munich cohort) with recently published Covid-19 related BALF sets. The raw count matrices and metadata from the Shenzhen48, Chicago49, and Berlin50 cohorts were downloaded and pre-processed separately with Scanypy (v1.6.0). Briefly, for each of the data sets cells that were present in the final provided object were retained. Additionally, we performed the number of UMI counts and genes per cell and applied the following thresholds: only cells with more than 200 genes and less than 15% mitochondrial transcripts were kept. We assessed the number of UMIs with sample-wise violin plots like the number of detected tran.

As T cell subtypes were of particular interest, we subdivided the data set to CD3E high cluster and refined the annotation after re-clustering and assessing of mean expression of CD8A, CD8B, and CD4 in the respective cluster. The expression matrices of each data set were normalized and log1p-transformed separately as described above for the Munich TAs. For a first lighter bath correction we defined the list of variable genes in a way that decreased cohort-specific effect as follows. First, highly variable genes were selected (flavor="cell_ranger") for each sample separately, returning the top 4000 variable genes per individual. For the Munich, Shenzhen, and Chicago cohorts, we considered a gene as highly variable if it is labeled as such in at least three patients of the respective cohort. As the Berlin cohort contained far more patients, we increased the threshold to six patients. After quality control the ambient RNA contamination was assessed and removed using SoupX with mostly default parameters, setting the contamination fraction manually to 0.3.

Next, the preprocessed count matrices from the individual data sets were merged and the highly variable genes were set to the intersection of the four cohort-wise lists. After excluding genes associated with the cell cycle, 1370 variable genes remained, which were used as input to PCA (n=50).

The published cell type assignments from each cohort were used further, the labels were harmonized as some annotations for the same cell type showed slight changes in spelling. Cells with unclear annotation were removed from the analysis (“Doublets” and “unknown, epithelial”). For visualization of the concatenated data sets, a UMAP and a batch-corrected neighborhood graph was constructed via BBKNNn using ten neighbors within each batch with cohort used as a batch key.

Computational data integration—T cell subtypes. The cells with the following annotations were used to subset to a T cell only data set: “CD3 T, CCR7+”, “Proliferating CD3 T cells, CD8+ T cells, Proliferating CD4 T cells, CD4 T cells, Proliferating CD4 T cells, Tregs” (Chicago cohort50) and “CTL, Treg” (Berlin cohort51). For the Berlin cohort, only T cells from BALF samples were used further, cells originating from nasal swabs are only shown in the data set encompassing all cell types. The cell type annotation for the Shenzhen and Berlin cohort did not provide a clear distinction between CD4 and CD8 T cells and was therefore refined in an additional step. After re-calculating of the principal components and Louvain clustering, manual examination of CD8A, CD8B, CD4A, CD3E expression enabled a more fine-grained annotation of the subtypes comparable with the Munich cohort data set. As re-calculating the variable gene list established on the full integrated data set, the PCA was re-calculated and the batch corrected neighborhood graph re-constructed (n_pcs=50, neighbors_within_batch = 20, batch_key = "data_set").

Hierarchical clustering of cell-type frequencies across Louvain clusters. Hierarchical clustering of cell-type frequencies across Louvain clusters was performed with Morpheus (https://software.broadinstitute.org/morpheus). Both Louvain clusters and cell types were clustered based on ‘one minus Pearson’ correlations.

NicheNet analysis. We performed NicheNet analysis on the scRNA seq reference cohort from Chicago using the R (version 3.6.3) packages nichener52 (version 1.0) and Seurat (version 3.2); To analyze cell-cell communication between Macrophages and CD4 or CD8 T cells respectively, we adopted the cell type annotation from the Chicago cohort and defined the subpopulations contained therein (MoAM1, MoAM2, MoAM3, TRAM1, and TRAM2) as sender cell types and all CD4 or CD8 T cells as receiver cell types, respectively. We then defined the genes comprising the different "ex vivo signatures" for CD4 and CD8 T cells as genes of interest for CD4 and CD8 T cells, respectively.

To analyze cell-cell communication between individual T cell subsets and TRAM or MoAM, respectively, we used the resulting 17 Louvain clusters from the integrated analysis as sender cell types and all TRAMs or MoAMs (see original annotation from the Chicago reference cohort) as receiver cell types. To define a gene set of interest, we performed differential expression testing at the gene level between TRAM1 vs. TRAM2 and immature MoAMs (MoAM1) vs. mature MoAMs (MoAM2 and MoAM3) using a Wilcoxon Rank Sum test with Seurat’s FindMarkers() function. We only included genes with a log-fold-change of >0.25, if they were expressed in >10% of all cells, and if their Holm-Bonferroni adjusted p values <0.05.

For all NicheNet analyses, we identified a list of potentially active ligands expressed by sender cell types and ranked them according to their ability (Pearson’s correlation coefficient) to predict the gene set of interest. We then selected the 12 top-ranked ones for subsequent analysis. The complete code for this analysis is reported in the Source Data file.

Software. Flow-cytometric data were analyzed with FlowJo v10.4.2. For visualization and some statistical analysis, GraphPadPrism (v8.4.3) was used. We performed analysis of scRNA seq data with CellRanger version 3.1.0 (10x Genomics), scarrypy (v1.6.0), scirpy (v0.4.0), diffflux (v0.7.4, 7), and SoupX (v1.3.6). Some hierarchically clustering analyses were performed with Morpheus (https://software.broadinstitute.org/morpheus; no version number indicated; version used as of September 2020). NicheNet analyses were performed with R (version 3.6.3) packages nichener (version 1.0) and Seurat (version 3.2). For code, see the Source Data file.

Reporting summary. Further information on research design is available in the Nature Research Reporting Summary linked to this article.

Data availability

All data generated or analyzed during this study are included in this article, its supplementary information files (Source Data file) and are available at NCBI GEO under the accession number GSE171037. Additional raw data are available from the corresponding authors upon reasonable request. The three independent reference cohorts were accessed as follows: “Shenzhen”: Single-cell landscape of bronchoalveolar immune cells in patients with COVID-19 (Liao et al.); “Berlin”: COVID-19 severity correlates with airway epithelium-immune cell interactions identified by single-cell analysis (Chua et al.). In addition, count and metadata tables containing patient identification, sex, age, cell type, and quality control metrics for each cell are available at FigShare: https://doi.org/10.6084/m9.figshare.12436517. https://figshare.com/articles/COVID-19_severity_correlates_with_airway_epithelium-immune_cell_interactions_identified_by_single-cell_analysis/12436517 Source data are provided with this paper.
Code availability
For scRNA seq data analysis algorithms see the "Methods" section and jupyter notebooks in the Source Data file. Additional information is available from the corresponding authors upon reasonable request.

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References
1. Guan, W. et al. Clinical Characteristics of Coronavirus Disease 2019 in China. N. Engl. J. Med. 382, 1708–1720 (2020).
2. Coronaviridae Study Group of the International Committee on Taxonomy of Viruses. The species Severe acute respiratory syndrome-related coronavirus: classifying 2019-nCoV and naming it SARS-CoV-2. Nat. Microbiol. 5, 536–544 (2020).
3. Thevarajan, I. et al. Breadth of concomitant immune responses prior to patient recovery: a case report of non-severe COVID-19. Nat. Med. 26, 453–455 (2020).
4. Chen, Z. & John Wherry, E. T cell responses in patients with COVID-19. Nat. Rev. Immunol. 20, 529–536 (2020).
5. Braun, J. et al. SARS-CoV-2-reactive T cells in healthy donors and patients with COVID-19. Cell 179, 572–579 (2019).
6. Le Bert, N. et al. SARS-CoV-2-specific T cell immunity in cases of COVID-19 and SARS, and uninfected controls. Nature 584, 457–462 (2020).
7. Braun, J. et al. SARS-CoV-2-reactive T cells in healthy donors and patients with COVID-19. Cell 179, 572–579 (2019).
8. Ferretti, A. P. et al. Article unbiased screens show CD8+ T cells of COVID-19 patients recognize shared epitopes in SARS-CoV-2. Nat. Biotechnol. 38, 13–19 (2020).
9. Grifoni, A. et al. Targets of T cell responses to SARS-CoV-2 coronavirus in humans with COVID-19 disease and unexposed individuals. Cell 181, 1489–1501.e15 (2020).
10. Sekine, T. et al. Robust T cell immunity in convalescent individuals with asymptomatic or mild COVID-19. Cell 183, 158–168.e14 (2020).
11. Neld, A. et al. SARS-CoV-2-derived peptides define heterologous and COVID-19-induced T cell recognition. Nat. Immunol. https://doi.org/10.1038/s41590-020-00808-x (2020).
12. Schattgen, S. A. et al. Linking T cell receptor sequence to transcriptional and diverse repertoire of human T cell receptors. Sci. Immunol. 5, eabe8063 (2020).
13. Stubbington, M. J. T. et al. T cell fate and clonality inference from single-cell analysis of the human naive and memory Th cell repertoire. Nat. Immunol. 14, 105–114 (2019).
14. Rydyznski Moderbacher, C. et al. Antigen-specific adaptive immunity to SARS-CoV-2 in acute COVID-19 and associations with age and disease severity. Cell 183, 996–1012.e19 (2020).
15. Meckiff, B. J. et al. Imbalance of regulatory and cytotoxic SARS-CoV-2–reactive T cells in COVID-19. Cell 183, 1340–1353.e16 (2020).
16. Ouchida, R. et al. A lysosomal protein negatively regulates surface T cell receptor expression by promoting CD3- and CD8-induced T cell-dendritic cell interaction. Nature 544, 890–895 (2016).
17. Chang, C.-H. et al. Posttranscriptional control of T cell effector function by glycolysis. Cell 153, 1239–1251 (2013).
18. Szabo, P. A. et al. Single-cell transcriptomics of human T cells reveals tissue heterogeneity and diverse repertoire of human T cell receptors. Nat. Biotechnol. 38, 270–274 (2020).
19. Yang, H. et al. Stress–glucocorticoid–TSC22D3 axis compromises therapy-induced antitumor immunity. Nat. Med. 25, 1428–1441 (2019).
20. Castellino, F. et al. Chemokines enhance immunity by guiding naïve CD8+ T cells to sites of CD4+ T cell-dendritic cell interaction. Nature 440, 890–895 (2006).
21. Chua, R. L. et al. COVID-19 severity correlates with airway epithelium–immune cell interactions identified by single-cell analysis. Nat. Biotechnol. 38, 970–979 (2020).
61. Kumar, B. V. et al. Human tissue-resident memory T cells are de
pseudotime robustly reconstructs lineage branching. Nat. Methods 13, 845–848 (2016).
62. Young, M. D. & Behjati, S. SoupX removes ambient RNA contamination from
droplet single-cell RNA sequencing data. Preprint at bioRxiv https://doi.
63. Lun, A. T. I., McCarthy, D. J. & Marioni, J. C. A step-by-step workflow for
low-level analysis of single-cell RNA-seq data with Bioconductor.
64. Polatksi, K. et al. BBKNN: Fast batch alignment of single cell transcriptsomes.
Bioinformat 36, 964–965 (2020).
65. Stuari, T. et al. Comprehensive integration of single-cell data. Cell 177, 1888–1902.e21 (2019).

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K.S., H.B.S., D.H.B., F.J.T., and B.S. conceptualized the study and developed methodolo-
gy; D.H.B., M.A., and N.J.L. developed and performed software analyses; K.S., D.S.F.,
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