nature portfolio

Corresponding author(s): Leila R. Martins and Claudia Scholl

Last updated by author(s): Jan 20, 2024

Reporting Summary

Nature Portfolio wishes to improve the reproducibility of the work that we publish. This form provides structure for consistency and transparency in reporting. For further information on Nature Portfolio policies, see our Editorial Policies and the Editorial Policy Checklist.

Statistics

Software and code

Policy information about availability of computer code

Single-cell RNA sequencing analysis:

Processing of scRNA-seq data. Raw sequencing data was processed with 10x Genomics Cell Ranger v3.1.0. Reads were aligned to a custom reference genome, which was created based on the mouse mm10 reference genome v1.2.0 provided by 10x Genomics. Firstly, sequences for transgenes Sgcb1a1 (3' of ER + 130 bp linker + 3' UTR of Scgb1a1), Sftpc (rtTA-M2 coding sequence) and DTA were added to the reference genome FASTA file. Subsequently, the endogenous Esr1 (genomic position Chr10:4611989-5005614) and 3' UTR of Scgb1a1 (genomic position Chr19:9083642-9083739) were masked from the genome. Then, three lines corresponding to the newly-added transgene sequences were added to the reference genome GTF file. Lastly, Cell Ranger was used to create the reference genome package from the modified FASTA and GTF files. SoupX v1.5.0 was used to remove ambient RNA contamination. To avoid underestimation of the global contamination fraction, manual gene lists were used for the sequencing runs of GFP+ mesenchymal cells on day 2 and 3 (Sftpc, Sftpa1, Sftpb, Sftpd, Dcn, Col1a1, Col1a2, Cldn3, Cldn18, Cldn2, Cldn4) and epithelial cells on day 4 (Sftpc, Sftpa1, Sftpb, Sftpd, Dcn, Scgb3a1, Foxj1) after tamoxifen administration in the SRC model. SoupX was otherwise run with default parameters. Further processing and analysis of count tables was performed with Seurat v3.2.1. Poor quality cells were filtered out based on high content of mitochondrial genes (4 to 7.5%, depending on the sample) and low total number of features (500 to 2500, depending on the sample), before integrating different samples. Detailed information for each scRNA-seq run can be found in Supplementary Data 1.

Sample integration, cell cycle regression, dimensionality reduction, clustering, and doublets exclusion. Individual samples were integrated with Seurat with IntegrateData() using 2,000 anchor features and integrating all common features between samples. Cell cycle phase was calculated by adapting the Seurat function CellCycleScoring() to use the GFP+ sorted cells as a reference. Cell cycle scores were then regressed out during data scaling with ScaleData() to mitigate the effects of cell cycle heterogeneity in the datasets from Fig. 3, 4, 7, Supplementary Fig. 3, 4, and 7. UMAP dimensionality reduction and nearest-neighbor graphs were calculated using the top 30 principle components. Cells were then clustered with FindClusters() with a resolution between 0.3 and 1.5, depending on cell number. Cell doublets were calculated with scDblFinder() (scDblFinder v1.2.0) using the default parameters and providing a vector of the runs id in the samples parameter. Clusters of cells composed of doublets were excluded from the analysis. Similar clusters were merged, taking into consideration the phylogenetic tree calculated with BuildClusterTree(). Cells were identified based on the expression of known marker genes and, when present, clusters composed of endothelial (Pecam+) or hematopoietic (Ptprc+) cells were excluded from the analysis. In the case of mesenchymal cell analysis, only clusters expressing Col1a1 were kept.

Differential gene expression and gene set enrichment analysis. Differential gene expression between different cell types (markers) was calculated with FindMarkers(test.use="roc", only.pos=TRUE, min.pct=0.2), and differentially gene expression between cells from non-injured and injured lungs was calculated with FindMarkers(test.use="MAST", min.pct=0.2). Common marker genes of DTA+ epithelial cells were calculated separately for downregulated and upregulated genes by intersecting the DEGs previously calculated for each population with FindMarkers(test.use="MAST", ident.1="DTA+_cell_type", ident.2=c("all populations excluding DTA+ cells", min.pct=0.2)). Only DEGs with a p_adj <0.05 were considered. Heatmaps for DEGs were generated with Seurat's function DoHeatmap(). GSEA was performed using Metascape v3.5 with a p-value cutoff of 10E-6. Activities of 14 pathways were inferred with PROGENy v1.10.0 using organism="Mouse", scale=FALSE and otherwise default values. Scores were scaled and centered using Seurat's ScaleData(). Heatmap showing pathway activity for each cell cluster at day 2 was drawn with ComplexHeatmap v2.4.3.

Transcriptome correlation between cell types. For every cell type combination of day 2 samples, Spearman's rank correlation coefficient was calculated from the average normalized expression of all genes. Heatmap was drawn with ComplexHeatmap v2.4.3.

Expression of human lung diseases signatures. To infer the expression of human lung diseases signatures in mouse epithelial cells, SRC mouse features were converted to their human orthologs using bioDBnet and a humanized Seurat object was generated using the same parameters as for the mouse object. Single-cell scores were calculated with AddModuleScore() using gene signatures for asthma, non-small cell lung carcinoma, and influenza from DisGeNET v7, and chronic obstructive pulmonary disease, COVID-19 bronchial epithelial cells, and pulmonary fibrosis from MSigDB v7.5.1 databases. Expression of the different signatures by each SRC epithelial population at day 0 and day 2 was drawn with the Seurat's RidgePlot() function.

Integration with COVID-19 dataset and DEGs analysis. Humanized Seurat objects from SRC mouse epithelial cells at day 0 and day 2 were generated by replacing mouse genes with their human orthologs. Conversion from mouse to human genes was done using bioDBnet. Epithelial cells from controls and COVID-19 patients, selected based on the author's "Epithelial cells" annotation were used to integrate with our mouse datasets following Seurat package guidelines. Seurat objects for each patient sample and each mouse run were normalized and FindVariableFeatures() was run before calculating anchors. To identify integration anchors, FindIntegrationAnchors() was run with a k.filter of 100 (due to the low cell number in some patient samples) and SRC mouse samples were used as reference. Integration anchors were then used to integrate the objects with IntegrateData(). The integrated Seurat object was scaled, UMAP dimensional reduction and nearestneighbor graphs were calculated using the top 30 principle components, and clusters were calculated with FindClusters() and a resolution of 0.5. Cell type identification of the COVID-19 dataset was done according to the authors' annotation ("cell_type_fine" identity class) and clusters were annotated based on the identity of the majority of the cells in the cluster. When several clusters with the same cell type were identified, a number was added as a suffix. The cluster containing mouse DTA+ cells, together with DTA+-like cells from the COVID-19 dataset, was annotated as DTA+-like cells. DEGs in DTA+-like cells were calculated with FindMarkers(test.use="MAST, min.pct=0.2, ident.1="DTA+-like cells") and considering only epithelial cells from COVID-19 patients (excluding cells from the SRC dataset and from human controls). Only DEGs with a p_adj <0.05 were considered.

Similarity to previously described epithelial cell types. Marker genes for all SfSRC mouse epithelial cell populations using all timepoints were calculated with FindMarkers(test.use="MAST", logfc.threshold=-Inf, min.pct=-Inf), and housekeeping genes listed in Laughney et al were excluded. Genes were ranked according to average log FC, and the top 50 genes from previously described epithelial cell types were used to calculate the normalized enrichment score (NES) for each SfSRC mouse epithelial population using fgsea v1.14.0 package.

Projection of cells between mouse models and experiments. To compare the cell populations present in different experiments, SingleCellExperiment objects were generated and cells from one experiment were projected onto cells from another experiment using scmapCell(). Cell assignment was done with scmapCell2Cluster() and drawn with getSankey() from scmap v1.10.0 package.

Expression of chemokines. Chemokine genes considered for analysis were taken from MGI GO TERM "Chemokine activity". scRNA-seq data to assess chemokine expression in homeostasis by lung cell types, including mesenchymal, immune, and endothelial cells, was taken from the

Mouse Cell Atlas (Supplementary Fig. 5c).

Cell-cell communication analysis. Intercellular interactions were inferred in mesenchymal (Fig. 2 cells) and epithelial cells (Fig. 4 cells) of the SRC model before (day 0) and after tamoxifen administration (day 2) with CellChat v1.1.0 following the official workflow and using standard parameters. The analysis was based on expression of ligand-receptor pairs from the CellChat mouse database, which we manually adjusted to exclude ligand-receptor pairs not supported by literature and to include interactions playing a role in intercellular junctions and mesenchymal cells of the lung (adjusted database is provided in Supplementary Data 14). Neuroendocrine cells were excluded from the analysis due to low cell numbers. For each timepoint, preprocessing of normalized count tables was performed with identifyOverExpressedGenes(), identifyOverExpressedInteractions() and projectData(). The cell-cell communication network was inferred using computeCommunProb(), which by default requires 25% of the cells per group to express the ligand or receptor gene. Summarizing analyses were performed with computeCommunProbPathway(), aggregateNet() and netAnalysis_computeCentrality(). The summed incoming and outgoing interactions strengths were obtained with netAnalysis_signalingRole_scatter() and scaled to the maximum summed interaction strength at the respective time point. For comparison of the signaling pathways between the two timepoints, the CellChat objects were merged with liftCellChat() and mergeCellChat().

Force-directed graph and PAGA analysis. Connectivities between different cell types were analyzed with the Scanpy package. PCA and a neighborhood graph were computed with pp.pca() and sc.pp.neighbors() using n_neighbors=10 and n_pcs=20. The force-directed graph was drawn with sc.tl.draw_graph(). For the PAGA analysis, the data was restricted to non-dividing cell clusters, on which the PCA and neighborhood graph were re-calculated using the same functions and parameters as above. Connectivities were quantified with tl.paga().

Diffusion maps. Diffusion maps restricted to cell type subsets of interest were calculated with Scanpy. The data was restricted to the cell type subset and the top 2,000 variable genes with a minimum count of 10. To avoid obtaining cell cycle-related genes, dividing cell clusters and cells in the G2/M or S phase were removed for the calculation of the top variable genes. PCA and the neighborhood graph were calculated with pp.pca() and sc.pp.neighbors() using n_neighbors=15 and n_pcs=20. The diffusion map was calculated with tl.diffmap().

RNA velocity. Spliced and unspliced read counts per gene were obtained with Velocyto v0.17.17 and merged with the pre-processed normalized and log-transformed count data from Seurat. To reduce the influence of possible variable kinetic rates between different cell types or states, RNA velocities were calculated separately on a reduced data set containing only cell types along the transition pathway using scVelo v0.2.2. First and second order moments were calculated using scvelo.pp.moments() with default parameters, velocities were calculated with scvelo.tl.velocity() in "dynamical" mode, and a velocity graph was constructed with scvelo.tl.velocity_graph(). The velocities were projected and visualized on diffusion map embeddings (see above) using scvelo.pl.velocity_embedding_grid(density = 0.5).

Trajectory inference and differential expression analysis. In the diffusion maps, trajectory analysis was performed with Monocle 3 v0.2.2 using default parameters, unless otherwise specified. The scale of the diffusion map DC values was adjusted by multiplying by 100. Cells in the diffusion map were clustered using cluster_cells() with parameters partition_qval=0.05 and num_iter=1. Trajectories were inferred using learn_graph(). Cells were assigned a pseudotime with the order_cells() function, for which root cells were manually chosen according to prior knowledge. The differential expression analysis was manually restricted to cells along the respective branch of interest and carried out using the function graph_test() with the parameter neighbor_graph="principal_graph". The expression was then scaled to the cell subset and smoothed using the loess() function in R with span set to 0.5. Heatmaps of the top 1,000 DEGs (sorted by q-value and Morans's I) were drawn with ComplexHeatmap v2.4.3. Mouse transcription factors in the DEGs were annotated with AnimalTFDBv3.0.

For manuscripts utilizing custom algorithms or software that are central to the research but not yet described in published literature, software must be made available to editors and reviewers. We strongly encourage code deposition in a community repository (e.g. GitHub). See the Nature Portfolio guidelines for submitting code & software for further information.

Data

Policy information about availability of data

All manuscripts must include a data availability statement. This statement should provide the following information, where applicable:

- Accession codes, unique identifiers, or web links for publicly available datasets
- A description of any restrictions on data availability
- For clinical datasets or third party data, please ensure that the statement adheres to our policy

Gene signatures for asthma, non-small cell lung carcinoma, and influenza were obtained from DisGeNET v7, and gene signatures for chronic obstructive pulmonary disease, COVID-19 bronchial epithelial cells, and pulmonary fibrosis from MSigDB v7.5.1 databases. Processed single-nuclei RNA-seq data from lungs of COVID-19 and control patients was obtained through the Gene Expression Omnibus (GEO) database under the accession code GSE171524. A manually curated database of ligand-receptor pairs was generated from the CellChat mouse database, and is provided in Supplementary Data 14. Chemokine genes considered for analysis were taken from MGI GO TERM "chemokine activity". scRNA-seq reads were aligned to a custom reference genome published with the DOI 10.5281/zenodo.10478745. Proteome ID UP000000589 from Uniprot was used for mass-spectrometry data analysis. The mass spectrometry proteomics data generated in this study have been deposited in the ProteomeXchange Consortium via the PRIDE partner repository with the dataset identifier PXD039508. The scRNA-seq data generated in this study have been deposited in the GEO database with under the accession code GSE223816.

Research involving human participants, their data, or biological material

Policy information about studies with human participants or human data. See also policy information about sex, gender (identity/presentation), and sexual orientation and race, ethnicity and racism.

Field-specific reporting

Please select the one below that is the best fit for your research. If you are not sure, read the appropriate sections before making your selection.

For a reference copy of the document with all sections, see nature.com/documents/nr-reporting-summary-flat.pdf

Life sciences study design

All studies must disclose on these points even when the disclosure is negative.

Reporting for specific materials, systems and methods

We require information from authors about some types of materials, experimental systems and methods used in many studies. Here, indicate whether each material, system or method listed is relevant to your study. If you are not sure if a list item applies to your research, read the appropriate section before selecting a response.

Antibodies

Antibodies used

Immunofluorescence:

Acetylated tubulin (Sigma, T7451, clone 6-11B-1, lot# 059M4812V), Agr2 (Proteintech, 12275-1-AP, lot# 58183), CC10 (Millipore, 07-623, lot# 3145007), CD34 (BD Biosciences, 553731, clone RAM34, lot# 7075697), Cyp2f2-Alexa Fluor 647 (Santa Cruz, sc-374540 AF647, clone F-9, lot# D1218), GFP-FITC (Rockland, 600-102-215, lot# 31007), Krt5 (Abcam, ab53121, lot# GR38774-37), Lamp3 (Dendritics, DDX0192-100, clone 1006F7.05, lot# DDX0192-030), Npnt (Invitrogen, PA547610, lot# VE2996317), Pdpn (Abcam, ab11936, clone RTD4E10, lot# GR3273681-3), SPC (Millipore, #AB3786, lot# 3537117), donkey anti-rabbit Alexa Fluor 568 (Invitrogen, A10042, lot# 1757124), goat anti-rat Alexa Fluor 568 (Invitrogen, A11077, lot# 1753597), and goat anti-hamster Alexa Fluor 647 (Invitrogen, A21451, lot# 1631002).

Animals and other research organisms

Policy information about studies involving animals; ARRIVE guidelines recommended for reporting animal research, and Sex and Gender in **Research**

Note that full information on the approval of the study protocol must also be provided in the manuscript.

Plants

Flow Cytometry

Plots

Confirm that:

 $\boxed{\mathbf{x}}$ The axis labels state the marker and fluorochrome used (e.g. CD4-FITC).

 \overline{x} The axis scales are clearly visible. Include numbers along axes only for bottom left plot of group (a 'group' is an analysis of identical markers).

 $\boxed{\mathbf{x}}$ All plots are contour plots with outliers or pseudocolor plots.

 \overline{x} A numerical value for number of cells or percentage (with statistics) is provided.

Methodology

 \overline{x} Tick this box to confirm that a figure exemplifying the gating strategy is provided in the Supplementary Information.