



Early View

Original article

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Alveolar macrophage transcriptomic profiling in COPD shows major lipid metabolism changes

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ONLINE DATA SUPPLEMENT

This article has an online data supplement.

TAKE HOME MESSAGE

AMs from COPD patients undergo GOLD grade-specific transcriptional reprogramming and acquire a complex activation profile. Among the observed changes are gene programs involved in lipid metabolism which translate into alterations in the AM lipidome. A better understanding of the crosstalk between the AM transcriptome and lipidome adds to the understanding of COPD pathogenesis and aids in the design of novel immunotherapeutic strategies.

ABSTRACT

Background: Immune cells play a major role in the pathogenesis of chronic obstructive pulmonary disease (COPD). Albeit established changes in distribution and cellular functions of major immune cells, such as alveolar macrophages (AMs) and neutrophils, their transcriptional reprogramming and contribution to the pathophysiology of COPD are still not fully understood.

Aim and methods: To determine changes in transcriptional reprogramming and lipid metabolism in the major immune cell type within the bronchoalveolar lavage fluid, we analyzed whole transcriptomes and lipidomes of sorted CD45⁺Lin⁻HLA-DR⁺CD66b⁻Autofluorescence^{hi} AMs from control and COPD patients.

Results: We observed global transcriptional reprogramming featuring a spectrum of activation states, including pro- and anti-inflammatory signatures. We further detected significant changes between COPD patients and controls in genes involved in lipid metabolism, such as fatty acid biosynthesis in GOLD2 patients. Based on these findings, assessment of a total of 202 lipid species in sorted AMs revealed changes of cholesteryl esters, monoacylglycerols and phospholipids in a disease grade-dependent manner.

Conclusions: Transcriptome and lipidome profiling of COPD AMs revealed GOLD grade-dependent changes, such as in cholesterol metabolism and interferon alpha and gamma responses.

INTRODUCTION

Chronic obstructive pulmonary disease (COPD) is characterised by progressive airflow obstruction, inflammation in the airways, and systemic comorbidities, such as cardiovascular diseases and diabetes [1]. It is a leading cause of morbidity and mortality worldwide [2], and induces a substantial and increasing economic and social burden [3, 4]. Current guidelines for COPD patient classification use the Global Initiative for Chronic Obstructive Lung Disease (GOLD) criteria on the basis of spirometry-estimated severity of airflow limitation and range from mild (GOLD grade 1) to very severe (GOLD grade 4) disease [5]. Cigarette smoking is the leading environmental risk factor for COPD, yet even for heavy smokers, fewer than 50% develop COPD during their lifetime, indicating that the disease initiates from a complex interaction between environment and genome. Some genetic factors, e.g. deficiency of alpha-1 antitrypsin (4) or single nucleotide polymorphisms in MMP12 (5) have been associated with the risk to develop COPD.

Innate immune cells are key players in protecting the lung from airway infections and their impairment plays a major role in COPD pathogenesis and exacerbation episodes [1, 8, 9]. Although changes in cellular distribution and functions within the alveolar space have been described in COPD before [10], these findings are far from being complete. Furthermore, the advent of omics technologies even extending to metabolomics [11], as well as a better understanding of cell type classification requires revisiting these aspects of innate immune cell biology of the alveolar space, both in healthy individuals and COPD patients. Alveolar macrophages (AMs) are described to be the most abundant cells in humans [12]. Under physiological conditions, AMs are the major cell type on the luminal surface of the alveolar space and are major regulators of the initiation and resolution of inflammation [13, 14] and

surfactant metabolism [15]. AMs catabolize pulmonary surfactants, which are composed of phospholipids and proteins and humans lacking functional AMs develop pulmonary proteinosis [16].

Recent reports have shown that in respiratory diseases, such as asthma, COPD and pneumonia a lipidomic remodeling of the bronchoalveolar lavage fluid (BALF) is observed, with changes in the levels of cholesterol, sphingomyelins, phospholipids and fatty acids being the most prominent [17–19]. In particular, the role of sphingolipids and cholesterol metabolism are believed to play a role in the pathogenesis of COPD [20, 21]. Nevertheless, changes of the lipid metabolism within AMs in COPD patients have not been addressed so far.

In this study, we hypothesized that transcriptional changes leading to altered lipid metabolism occur in a disease grade-dependent manner. Using multi-colour flow cytometry (MCFC), we defined AMs as the major cell type in COPD patients for which we provide clear evidence of global transcriptional reprogramming, which differed between GOLD grade 2 and GOLD grade 3/4 COPD patients. Among the major alterations in the AM transcriptome of COPD patients, we identified genes associated with lipid metabolism, which was linked to significant changes in several lipid species by lipidomics analysis.

METHODS

Human specimens

Human studies were approved by the ethics committees of the University of Bonn and University hospital Bonn (local ethics vote 076/16). All patients provided written informed consent according to the Declaration of Helsinki before specimens were collected. Patients with COPD were diagnosed and stratified according to the guidelines of the global initiative for chronic obstructive lung disease (GOLD) [5]. Eligible patients were aged 18 years or older and were either current, past or non-smokers (Table E1). Age-matched individuals suffering from chronic idiopathic cough, demonstrating an exquisitely sensitive cough reflex without underlying pathology [22], served as control donors. Patients with other pulmonary diseases (termed other (Fig. 1A)) were diagnosed as asthma, ACO, bronchiectasis, cancer, fibrosis, pneumonia and sarcoidosis (Table E2), but were excluded from further evaluation within this study.

Bronchoscopy procedure

Bronchoscopy was performed as a part of the diagnostic workup by two bronchoscopists through oral access and with light conscious sedation and was performed in the middle lobe or, if not accessible, the lingular lobe. Warmed saline (6 syringes of 20 ml each) was instilled into the airways to enable BALF recovery.

BALF processing

Human BALF was obtained from all patients included in the study (control, COPD, other) through bronchoscopy. BALF specimens were washed with PBS, suspended with 0.02% EDTA-2Na and washed again for final re-suspension with 2% FCS/1 mM EDTA. CD45⁺Lin⁻HLA-DR⁺CD66⁻Autofluorescence⁺ AMs were sorted using a FACS

Aria III cell sorter (BD Biosciences, USA).

Cell counting

Total cell counts were determined with (1:5) Trypan Blue exclusion (Sigma-Aldrich) under an optical microscope. BALF cells were diluted 1:10 in the Trypan Blue solution and counted in a Neubauer haemocytometer.

Flow cytometry/FACS

Single-cell suspensions were stained with Live/Dead yellow fluorescent dye (ThermoFisher, USA) for 15 min at room temperature and were washed with PBS at 300xg for 5 min at 4°C. They were then re-suspended in 100 ul PBS and blocked with 5 ul human FcR blocking reagent (Miltenyi, Germany) for 15 min on ice and were subsequently stained with the listed anti-human antibodies (Table E4) in buffer containing PBS, 2% FCS, 1 mM EDTA for 30 min on ice. Cells were spun at 300xg for 5 min at 4°C and re-suspended in buffer containing PBS, 2% FCS, 1 mM EDTA for analysis. Data acquisition was performed on a FACS Aria III cell sorter (BD Biosciences, USA). Analysis was performed with FlowJo v.10 software (Tree Star, USA).

Cytospin preparation

Cytospins were obtained by centrifuging 2×10^5 cells in 200 ul PBS on microscope slides at 20% power for 5 min. Excess buffer was carefully discarded and slides were air dried for 3 min followed by fixation with 100% methanol for 5 min at 4°C. The slides were subsequently washed with PBS and stained with 1:20 Giemsa solution (Sigma, USA) for 25 min at room temperature. A final rinsing step with H₂O and air

drying before mounting followed. Cell morphology was examined by microscopic evaluation of stained cells using an Axio Lab A1 microscope (Zeiss, Germany).

RNA extraction and library preparation

Total RNA was isolated from human AMs with the miRNeasy Micro kit (Qiagen, Germany) according to the manufacturer's protocol. cDNA libraries were prepared from 5 ng total RNA with the SMART-seq2 protocol [23] and were tagged with the Nextera XT kit (Illumina, USA). Library size selection was carried out with AMPure beads (Beckman-Coulter, USA). Libraries were sequenced for SR 75 cycles on a NextSeq500 system (Illumina) using High Output v2 chemistry. Base call files were converted to fastq format and demultiplexed using bcl2fastq v2.20.

Data pre-processing and RNA sequencing analysis

The 75 bp single-end reads were aligned to the human reference transcriptome hg38 from UCSC by kallisto v0.44.0 using default parameters. Data were imported into DESeq2 (v.1.10.1; [24]) using the TXimport (v1.2.0, [25]) package. DESeq2 was used for the calculation of normalized counts for each transcript using default parameters. All normalized transcripts with a maximum over all group means lower than 10 were excluded resulting in 33,032 present transcripts. Unwanted or hidden sources of variation, such as batch, sex and smoking status were removed using the sva package [26]. The normalized rlog transformed expression values were adjusted according to the five surrogate variables identified by sva using the function removeBatchEffect from the limma package [27]. DE genes were defined by a p-value cut-off of 0.05 and an adjusted p-value (IHW) < 0.5 (independent hypothesis weighting).

Gene set enrichment analysis (GSEA)

GSEA [28] was performed on all present genes of the dataset using the gene ontology set of biological processes. Information of gene ontology was obtained from the biological process gene set “c5.bp.v7.0.symbols.gmt”, downloaded from the Molecular Signatures Database (MSigDB). All present genes were used as background (universe).

Linear support vector regression

Linear support vector regression [29] was employed to characterize the relative contribution of 28 different activation signatures derived from [30] to the control and COPD patients (1,000 permutations).

Filtering for TFs, epigenome, surfaceome and secretome

All present transcripts were filtered and sorted by their variance in the dataset. The 20 most variable genes of each category were selected and visualized in heatmaps. TF lists were extracted from [31], the epigenome gene list was derived from the literature, surface and secretome markers were extracted from the Human Protein Atlas [32, 33].

Construction of co-expressed network analysis – automated (CoCena²)

CoCena² was performed to elucidate similarities and differences within the gene expression patterns of the three different patient groups. Pearson correlation was calculated on the 6,000 most variable genes within the dataset using the R package Hmisc (v4.3-0; [34]). Data were filtered for significant (p -value < 0.05, Bonferroni

correction $p < 0.05$) and positive (r -value > 0) correlation values. The Group Fold Change (GFC) was calculated for each gene and each condition on the inverse logarithmic count data using the R package gtools (v3.8.2; Unbiased clustering was performed using the R package igraph (v1.2.4.1; [35]). The clustering algorithm “cluster_louvain” was selected as it achieves the highest modularity score. Clusters with less than 35 genes are not shown. Network generation was performed with the R package igraph. The network information was imported to and exported from Cytoscape using the R package RCy3 (v2.6.2; [36]).

Biological function-related bioinformatic analysis of network modules

GSEA was performed on the patient group-related modules identified by CoCena² using the R package ClusterProfiler (v3.12.0; [37]). Information of hallmark genes was obtained from the hallmark gene set “h.all.v6.1.symbols.gmt”, downloaded from the Molecular Signatures Database (MSigDB). All genes present in the network were used as background (universe).

Lipidomics

Sorted AMs (5×10^4) pelleted and frozen at -80°C until analysis. Extraction mix (Chloroform 1:5 methanol-containing internal standards was spiked to the pellets before sonication. Samples were treated with chloroform and 1% acetic acid, the lower phase was transferred after centrifugation, and let evaporate in the vacuum concentrator (45°C for 10 min). After addition of spray buffer and sonication, samples were analyzed separately with a Thermo Q Exactive Plus spectrometer equipped with the HESI II ion source for shotgun lipidomics.

Lipidomics analysis

LipidXplorer software was used for analysis using custom mfql files to identify sample lipids and internal standards. Absolute amounts were calculated using the internal standard intensities followed by normalization on the sum of all measured lipid species per sample. %mol values were averaged for each patient group, log₂-transformed and then used for fold change calculations. CoCena² was used to find patient group-specific co-regulated lipid species using Pearson correlation and clustering using the “cluster_louvain” algorithm.

Statistics

A two-tailed Welch’s unpaired t test was used to analyze data from two groups. Equality of population variance was assessed with the F-test statistic for two independent groups. A non-parametric Wilcoxon test was used to perform a pairwise comparison between patient groups for all enriched macrophage activation signatures in Fig. 3F. For more than two groups, normality and homoscedasticity were first assessed using the Shapiro-Wilk and Levene tests in R (v3.6.1). A non-parametrical Kruskal-Wallis test with Dunn’s multiple correction post hoc was used in Fig. E3 because the data did not follow a normal distribution. Statistical significance was inferred when $p < 0.05$.

For a full list of the methods an Online Supplement is provided.

RESULTS

Macrophages are the most abundant cell type in the alveolar space in COPD

We first evaluated the cell type distribution in the BALF to ensure that AMs are the most abundant cell type in control and COPD samples, the latter of which an enrichment of neutrophils had been postulated [38]. We performed MCFC integrating marker to determine all major immune cell types expected within the alveolar space [39]. Individuals with chronic coughing served as controls (Table E1). Only BALF samples of the highest quality following quality criteria established previously for the processing of BALF [40], such as recovery rate higher than 30% and absence or minimal blood/mucus contamination were included in the study (Fig. 1a). Out of 177 screened BALF samples in the clinic, 72 were derived from COPD patients, 44 from control individuals, while patients suffering from asthma, asthma-COPD overlap, bronchiectasis, cancer, fibrosis, pneumonia or sarcoidosis were excluded (Table E2). Sixty-nine patients (36 COPD and 33 controls) finally qualified for further analysis (Table E3).

We stained for markers of the myeloid cell compartment (Fig. 1b; Table E5), whereas lymphocytes were labelled with antibodies against CD3, CD19 and CD56 (Fig. 1b). Our data show that AM numbers undergo a non-significant increase in COPD patients, whereas we could detect a statistically significant upregulation ($p < 0.05$) in the neutrophil numbers of GOLD3/4 grade patients compared to controls (Fig. 1c). Eosinophil and monocyte numbers varied widely within groups and reached no significance, whilst mast cells were found to be significantly higher ($p < 0.05$) in GOLD3/4 compared to GOLD2 COPD patients (Fig. 1c).

Table E3. Clinical characteristics of control and COPD patients

	Flow cytometry		RNA-sequencing		Lipidomics	
	Control (n=29)	COPD (n=30)	Control (n=6)	COPD (n=9)	Control (n=7)	COPD (n=8)
Sex	11M 18F	21M 9F	5M 1F	8M 1F	4M 3F	5M 3F
Age (years)	56 ± 11	65 ± 9	53 ± 9	64 ± 9	51 ± 15	59 ± 7
GOLD grade	-	17GOLD2, 10GOLD3, 3GOLD4	-	5GOLD2, 2GOLD3, 2GOLD4	-	4GOLD2, 4GOLD3, 0GOLD4
GOLD group	-	0A, 16B, 14D	-	1A, 6B, 2D	-	0A, 3B, 5D
FEV1/FVC	86 ± 11	GOLD2: 63 ± 6 GOLD3: 59 ± 8 GOLD4: 66 ± 1	81 ± 4	GOLD2: 67 ± 3 GOLD3: 66 ± 1 GOLD4: 52 ± 1	81 ± 6	GOLD2: 67 ± 1 GOLD3: 61 ± 11
FEV1%	95 ± 13	GOLD2: 65 ± 9 GOLD3: 40 ± 6 GOLD4: 32 ± 9	94 ± 20	GOLD2: 68 ± 7 GOLD3: 48 ± 1 GOLD4: 28 ± 1	99 ± 15	GOLD2: 71 ± 11 GOLD3: 37 ± 7
Smoking history	5S, 7ex-S, 17NS	GOLD2: 7S, 10ex-S, 0NS GOLD3: 1S, 9ex-S, 0NS GOLD4: 0S, 3ex-S, 0NS	0S, 2ex-S, 4NS	GOLD2: 2S, 2ex-S, 1NS GOLD3: 2S, 0ex-S, 0NS GOLD4: 1S, 1ex-S, 0NS	0S, 2ex-S, 5NS	GOLD2: 2S, 2ex-S, 0NS GOLD3: 1S, 3ex-S, 0NS
Packyears	29 ± 20	58 ± 40	2 ± 3	51 ± 38	4 ± 9	69 ± 33
LAMA	1Y 28N	26Y 4N	0Y 6N	7Y 2N	0Y 7N	8Y 0N
LABA	4Y 25N	26Y 4N	0Y 6N	7Y 2N	0Y 7N	8Y 0N
ICS	4Y 25N	8Y 22N	0Y 6N	1Y 8N	0Y 7N	3Y 5N
Death	0Y 29N	3Y 1N/A 26N	0Y 6N	0Y 9N	0Y 7N	0Y 8N
Hospitalizations	0Y 29N	12Y 1N/A 17N	0Y 6N	3Y 6N	0Y 7N	2Y 6N
Exacerbations	0Y 29N	18Y 1N/A 11N	0Y 6N	6Y 3N	0Y 7N	4Y 4N

Lymphoid cells were of much lower frequency and using a second panel for lymphoid cell markers (Fig. S1a; Table E5), we observed that only innate lymphoid cells (ILCs) were statistically significantly ($p < 0.05$) changed in all COPD samples (Fig. S1b-c), with a similar trend when taking GOLD grades into account (Fig. S1b). Within ILCs, ILC1s were the only significantly increased ($p < 0.05$) ILC population in COPD patients (Fig. S1d). Cell type classification was also confirmed on sorted cells by Giemsa staining of cytopins (Fig. 1d). Collectively, AMs are the most abundant cell type in BALF, which was then our focus for subsequent transcriptome and lipidome analyses.

Transcriptional changes in AMs within the alveolar space of COPD patients

To elucidate molecular changes of AMs as the most prevalent cells within the alveolar space, we sorted $CD45^+Lin^-HLA-DR^+CD66b^-Autofluorescence^{hi}$ AMs from the BALF of 9 COPD and 6 control patients and generated whole transcriptomes by RNA sequencing (Fig. 2a). Principal component analysis (PCA) of all present genes (Fig. 2b) and hierarchical clustering of the 25% most variable genes within the dataset (Fig. S2a) revealed a clear disease grade-dependent structure within the data suggesting significant differences between COPD GOLD2, GOLD3/4, and control samples.

Next, we calculated differentially expressed (DE) genes between GOLD2 or GOLD3/4 COPD and control patients, respectively. There were 563 DE genes (229 up, 334 down, $p < 0.05$, $FC > 1.5$) between GOLD2 and control, 1,456 (618 up, 838 down, $p < 0.05$, $FC > 1.5$) between GOLD3/4 and control, and 1,147 (572 up, 575 down, $p < 0.05$, $FC > 1.5$) between GOLD2 and GOLD3/4 COPD patients (Fig. 2c), which we visualised in Volcano plots for all pairwise comparisons (Fig. 2d).

We first assessed overall transcriptional changes. We provide information for

the top 20 altered transcription factors (TFs), epigenetic modulators, cell surface molecules (surfaceome) and soluble mediators as micro-environmental interactors (Fig. S2b-e). Upregulated TFs included *ETS2* in COPD patients consistent with its function as a biomarker for loss of lung function [41] (Fig. S2b). Consistent with the reported dysregulation of histone deacetylase (HDAC) and sirtuin epigenetic signalling in AMs from COPD patients [42–45], the expression of histone modifying enzymes *HDAC9* and *SETD1A* was downregulated in GOLD3/4 COPD (Fig. S2c). Regarding the surfaceome of the AMs, we measured decreased antigen presentation molecules (*HLA-DQA2* and *CD1B*) [46, 47] and *CCR2* expression in GOLD3/4 COPD patients (Fig. S2d). Notably, expression of the ligand chemokine to *CCR2*, *CCL2*, was elevated in the secretome-associated gene set of GOLD3/4 COPD patients, similar to other members of the CC family of chemokines, including *CCL8* and *CCL20* (Fig. S2d), highlighting the role of chemokines in COPD pathophysiology [48]. Finally, we detected the downregulation of *MMP7* and *MMP9* in GOLD3/4 COPD patients, with *MMP12* being expressed significantly higher only in GOLD2 COPD patients (Fig. S2e), in agreement with the role of metalloproteinases in the progression of COPD [49–52].

Activation state analysis indicates changes in lipid metabolism

We have previously reported that macrophage activation follows a multi-dimensional model of cell activation [30]. However, for AMs in COPD, it has been proposed that AMs in COPD follow a dual polarization model with deviation towards an anti-inflammatory phenotype [47, 49, 53, 54] with no hints on alterations in lipid metabolism. To analyse how the observed transcriptional changes in COPD AMs related to our multi-dimensional model of activation states, we performed linear

support vector regression utilizing our previous human macrophages activation spectrum model based on 29 conditions [30] (Fig. 3a). Our activation spectrum model could be grouped into 9 major activation programs (c1-9) and were used here as the bait to deconvolute the AM transcriptomes from COPD and control patients. The COPD and control transcriptomes were enriched in a spectrum of activation signatures ranging from pro-inflammatory to anti-inflammatory, as well as those extracted from fatty acid-stimulated macrophages (c5 module signature) that show deviations in lipid metabolism. AMs from GOLD2 COPD patients exhibited significantly lower enrichment ($p < 0.05$) of the c4 module signature (P3C/PGE₂, P3C and PGE₂ stimulation) compared to GOLD3/4 COPD and control patients and c8 module signatures (TNF- α /P3C, TNF- α and P3C stimulation) in comparison with GOLD3/4 COPD patients (Fig. 3a). In addition, COPD GOLD2 AMs showed a higher enrichment ($p < 0.05$) of the c5 module signatures (LA, LiA, OA, PA, and SA stimulation) compared to AMs from control patients (Fig. 3a).

Based on these results indicating potential changes in lipid metabolism associated-genes, we next performed gene set enrichment analysis (GSEA) for either GOLD2 or GOLD3/4 COPD patients compared to controls (Fig. 3b-c). Lipid-related gene sets, such as fatty acid catabolic process, fatty acid oxidation and regulation of cholesterol biosynthetic process were enriched in AMs from GOLD2 COPD patients (Fig. 3b). AMs from GOLD3/4 COPD patients presented with enrichment in cholesterol and lipid storage compared to controls (Fig. 3c).

To highlight the genes that are involved in the lipid-associated phenotype of COPD AMs, we visualised the 20 most variable genes for the gene ontology term “fatty acid metabolism” of the c5 module from Fig. 3a (Fig. 3d) and “fatty acid catabolic process” from Fig. 3b (Fig. 3e). Several genes which are involved in

cholesterol homeostasis were dysregulated in COPD patients. For example, enzymes involved in fatty acid metabolism, such as *ACAT2*, *FAAH*, *MLCYD* and *ACOX2* or enzymes that synthesize diacylglycerols (*LPIN3*) were expressed higher in GOLD2 COPD patients. On the contrary, the acyltransferase *CRAT* and the triglyceride synthesis enzyme *LPIN2* were overexpressed in GOLD3/4 COPD patients. Fatty acid synthase *FASN* and the anti-inflammatory TF *ATF3* [55, 56] were both downregulated in COPD patients irrespective of GOLD grade (Fig. 3d-e). These findings strongly support that AMs do not follow a simple polarization model, but rather display a multi-activation phenotype with a shift towards lipid activation signatures.

Co-expression analysis reveals changes in cholesterol homeostasis in COPD

Co-expression network analysis is an alternative to statistical methods describing changes in transcriptome data, such as the calculation of differentially expressed genes based on a set fold change and p-value [57]. To further investigate active gene programs in AMs, we performed gene co-expression analysis using CoCena² (construction of co-expression network analysis – automated) (Fig. 4a). The clustering of the genes within the constructed network led to the identification of groups of transcriptionally similarly regulated genes within the dataset. The mean GFC of these gene modules in GOLD2, GOLD3/4 COPD and control patients were visualised in a heatmap (Fig. 4b). We detected 11 modules, three of which demonstrated GOLD grade-associated average expression; for instance, modules 7 and 8 had a higher GFC in GOLD2 COPD patients, modules 3 and 4 were GOLD3/4-related, whilst modules 9, 10 and 11 had a higher GFC in AMs from control patients.

Next, GSEA was applied to concatenated modules per disease group (control: 1,

2, 6, 9, 10, 11, GOLD2: 5, 7, 8, GOLD3/4: 3, 4) to link the co-expressed genes to biological processes (Fig. 4c). While genes of control patients were enriched in apical junctions, genes from the modules enriched in AMs derived from GOLD2 patients suggested changes in cholesterol homeostasis in addition to the findings based on statistical analysis (Fig. 3). However, GSEA of modules enriched in AMs derived from GOLD3/4 patients were not revealing any enrichment of terms related to lipid metabolism, but rather terms associated with cell cycle and the secretion of pro-inflammatory cytokines.

The co-expression of genes associated with cholesterol homeostasis were not previously described to be altered in AMs of COPD patients. Therefore, we investigated the GOLD2-associated modules in more detail and identified genes involved in sterol biosynthesis (*DHCR7*, *SQLE*), cholesterol transportation to cells (*LDLR*) and fatty acid metabolism (*FADS2*) (Fig. 4d). In contrast, genes of the interferon response (*CXCL10*, *IFIT3*, *IFITM1*, *IFITM3*, *OAS1*, *RSAD2*, and *ISG15*) (Fig.4e) and genes involved in the G2M checkpoint including the proliferation marker *MKI67*, cyclin-dependent kinases (*CDK1*) and DNA replication machinery (*TOP2A*, *CENPA*) (Fig.4f) were highly expressed in GOLD3/4 AMs.

In summary, AMs derived from the BALF of COPD patients show numerous transcriptional changes that suggest broad reprogramming including genes involved in lipid metabolism with different functionalities that follow GOLD grade-specific patterns.

Lipidome analysis of AMs reveals GOLD-specific changes in COPD

The AMs are the major cell type in the alveolar space being involved in lipid metabolism, e.g. of the surfactant [58]. Performing a transcriptome analysis of AMs

derived from COPD and control patients using two different mathematical approaches identified reprogramming of lipid metabolism. To elucidate whether the changes we observed in these cells' transcriptomes in COPD is associated with changes in their lipidome, CD45⁺Lin⁻HLA-DR⁺CD66b⁻Autofluorescence^{hi} AMs were sorted from the BALF of 8 COPD and 7 control patients and were used for mass spectrometry-based lipidomics (Fig. 5a). Seventeen different lipid classes including a total of 202 lipid species were quantified. Glycerophospholipids, especially the phosphatidylcholines (PC), alongside phosphatidylethanolamines (PE), phosphatidylinositols (PI) and phosphatidylserines (PS), the sphingolipids (ceramides (Cer) and sphingomyelins (SM)) and the monoacylglycerols (MAG) constituted the major lipid mass of AMs (Fig. 5b). Comparison of the AM lipidome of COPD with that of control patients indicated most prominent changes in the cholesterol ester (CE) and MAG classes (Fig. 5b) and quantification of the mean GFC revealed disease severity-specific changes in the analysed lipid classes (Fig. 5c). In accordance with the predicted change in cholesterol metabolism, AMs from GOLD2 COPD patients exhibited an upregulation of CE, but also downregulation of hexosylceramides (HexCer). In contrast, AMs from GOLD3/4 COPD patients showed an increase in MAG and diacylglycerols (DAG) and a decrease in the PC class. GOLD grade-specific patterns were reflected as well on the single lipid species level, revealing the diverse changes within each lipid class (Fig. 5d-e), all in all prompting us to investigate this in greater detail.

For this purpose, we determined lipid-lipid level correlations using the CoCena² pipeline. We identified nine different modules encompassing similarly regulated lipid species across the disease groups (Fig. 5f). Modules 1, 2 and 3 showed enriched

lipid species in GOLD2, whereas module 8 encompassed lipid species specifically enriched in GOLD3/4 COPD patients (Fig. 5f).

A closer look at the GOLD2-specific modules revealed enrichment for many unsaturated PC (e.g. PC(32:2, 36:3, 38:4, 38:5, 40:4) and CE (CE(16:1, 18:0, 18:1, 18:2, 18:3, 20:4)), as well as a few SM (e.g. SM(18:0, 22:1, 24:0, 24:2)), lysophosphatidylcholines (LPC) (e.g. LPC(20:4, 22:5, 22:6)) and Cer, such as Cer(d18:1/24:0) or (d18:1/24:1) (Fig. 5g). On the other hand, distinct lipid species were correlated in the module specific for GOLD3/4 AMs, which showed an accumulation of neutral lipids, such as saturated MAG (MAG(16:0, 18:0)) and DAG (DAG(32:0, 34:0, 36:0)) (Fig. 5h). Taken together, AMs from COPD patients display changes in their lipidome, which, in addition to their transcriptome, are GOLD grade-associated and could constitute a hallmark in the pathogenesis of COPD.

DISCUSSION

Chronic inflammatory diseases such as COPD are associated with functional and transcriptional alterations of immune cells involved in the pathophysiological processes and disturbances of organ-related homeostatic functions, e.g., surfactant biology in the lung. Here we focused on the most abundant immune cell type in the alveolar space, namely the alveolar macrophage to determine transcriptional changes particularly in those genes associated with lipid metabolism. By defining the AM transcriptomes, we observed numerous GOLD grade-specific changes in COPD patients. Evident changes in gene expression related to lipid homeostasis were further evaluated by lipidome profiling of AMs, which demonstrated that prominent lipid changes correlate with disease severity.

We focused on AMs, the most prevalent immune cell in the alveolar space of COPD patients and investigated their transcriptomes. Previously, AMs were shown to convert to an anti-inflammatory phenotype in COPD smokers based on the simple paradigm of M1,M2 polarization [47, 49, 54]. Additionally, a recent article found that some of those cells may carry a dual M1,M2 pattern in severe COPD [53]. However, we have previously demonstrated that macrophages follow a multi-dimensional model of activation [30]. Comparison of these various activation signatures with the transcriptome of AMs from COPD patients revealed that these cells can be better described by various activation signatures (including PGE₂ (c4, c8) and lipid (c5) signatures). To further explore the overall transcriptional changes in AMs derived from COPD patients, we provide the data for further easy inspection at [FASTGenomics.org](https://www.fastgenomics.org). Here we focused on the changes related to lipid metabolism.

AMs maintain lung function by supporting the air-liquid interface on the alveolar surface, which, when compromised, results in augmented surface tension and

pulmonary proteinosis [16]. It has been shown that lipid homeostasis in COPD is perturbed in both humans [21] and cigarette smoke-induced mouse models [59]. In addition, decreased BALF levels of cholesterol, SM and phospholipids correlate with loss in lung function in COPD patients [17]. Our analysis shows that AMs from GOLD2 COPD patients are enriched in PC and cholesterol esters, and express higher levels of lysosomal lipase *LIPA*, which suggests that in mild severity stages, AMs may contribute to the decrease in surfactant lipids in the alveolar space by increasing their surfactant catabolism rate. In contrast, in more severe stages, AMs are characterised by the enrichment in saturated MAG and DAG, which indicates a degradation defect is very likely due to the accumulation of glycerolipids.

Recently, lipidome analysis of perturbed macrophages showed that changes in lipid composition correlate with functional responses [60]. AMs exhibit a foam-like phenotype with augmented TGF- β secretion in response to silica dust and cholesterol uptake [61]. Other findings were changes in cholesterol biology. Here one could postulate that the balance between cholesterol synthesis and the liver X receptor (LXR) pathway acts as a rheostat that controls AM inflammatory responses. In GOLD2 patients, cholesterol synthesis was upregulated and LXR signaling was repressed. In contrast, in GOLD3/4 COPD patients, cholesterol synthesis was downregulated which would be consistent with the upregulation of the LXR pathway and the induction of lipogenesis [62]. This switch could have implications in AM biology in COPD, as LXR activation confers anti-viral protection [63] and inflammation resolution [64].

In addition, the observed heightened levels of CE and SM in AMs from GOLD2 COPD patients may be responsible for the dysregulation of AM functionalities, such as efferocytosis of apoptotic cells as shown before in rats exposed to cigarette

smoke [65]. Dampened PI levels curtail viral infections in mice via TLR pathway inhibition [66]. Our data provide the enriched interferon responses as additional mechanistic insight in AMs from GOLD3/4 patients.

As with every exploratory study, some of the limitations of our study need to be mentioned. First, the control cohort consisted of patients suffering from chronic idiopathic cough, which might be regarded as a potential confounder given the presence of lipid laden macrophages in human BALF samples [67]. However, the assessment of these patients demonstrated that they suffered from an exquisitely sensitive cough reflex without any underlying lung pathology. On average, the control group was also younger than the COPD group and too small to thoroughly investigate differences between smokers and non-smokers in COPD and control patients. To alleviate any confounding age, smoking status effects in our transcriptome analysis, we computationally removed technical and unknown variance before downstream analysis. We suggest that any effect of age or smoking on high-dimensional data, including lipidomics might be indeed interesting questions for future studies.

Taken together, although the numbers of AMs are not significantly changed in the alveolar space in COPD, we conclude that they undergo transcriptional reprogramming that leads to GOLD grade-dependent changes in lipid metabolism. Elucidation of the concomitant alterations in the transcriptome and lipidome of alveolar macrophages aids the understanding of their role in COPD and provides druggable molecular pathways, such as cholesterol metabolism and interferon alpha and gamma responses.

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AUTHOR CONTRIBUTIONS

WF, TSK and KB collected samples and performed experiments. KH carried out RNA sequencing. CT carried out mass spectrometry for lipidomics. WF, TSK, TU, LH, RK, SWH, MO, JH and ACA analyzed data. CP and DS recruited patients. DS and JLS designed study. WF, TSK, and JLS wrote the manuscript with input from all authors. All authors were involved in discussing the results of the study.

CONFLICT OF INTEREST DECLARATION

The authors declare no conflicts of interest.

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38.

FIGURE LEGENDS

Fig. 1 - Identification of lymphoid immune populations in the BALF of COPD and control patients. Schema of the pipeline for collection and processing of human bronchoalveolar lavage fluid samples. Of 177 BALF samples, 69 satisfied the quality criteria (>30% recovery rate and no blood and/or mucus contamination and were included in the study for multiple colour flow cytometry, transcriptomics and/or lipidomics. Sixty-one patients suffering from asthma, ACO, bronchiectasis, cancer, fibrosis, pneumonia or sarcoidosis were excluded from the study (a). Representative multi-colour flow cytometry analysis of the myeloid compartment of a control patient (b). Absolute numbers of myeloid immune cells in the BALF of control, GOLD2 and GOLD3/4 COPD patients calculated with traditional gating. Data are from 8-29 patients per group except for mast cells GOLD3/4 (n=2) and re represented as mean \pm SD (c). Data are represented as mean \pm SEM and were analysed with an unpaired two-tailed student t-test, * $p < 0.05$. Giemsa staining of cytospins for sorted BALF myeloid cell types (d). Black bars indicate 10 μ m.

Fig. 2 – Whole transcriptome analysis of AMs reveals lipidomic dysregulation in COPD patients. Schematic representation of the bioinformatics workflow and methods used for the transcriptome analysis of 15 RNA-seq samples from GOLD2, GOLD3/4 COPD and control patients (a). PCA of all 33,032 present transcripts (b). Distribution and amount of DE genes (c). Volcano plots of the comparisons GOLD2 vs control, GOLD3/4 vs control and GOLD2 vs GOLD3/4. Upregulated genes are marked in red, downregulated genes in blue. Fold change cut-off was set to 1.5, adjusted p-value cut-off was set to 0.05 (d).

Fig. 3 – Overlay of human macrophage activation states in AMs from COPD patients show lipid term enrichment. 29 macrophage activation signatures from [30] were used as input to identify the relative fraction of these activation signatures in COPD and control patients. Grouping of activation signatures in 9 clusters was used as proposed in [30]. Data were statistically analysed with the non-parametrical Wilcoxon test, $* < 0.05$ (a). GSEA using the gene ontology (GO) database filtered for “fat” and “lipid” as reference signatures. Normalized enrichment scores (NES) and enrichment p-values for the 5 most enriched GO terms for the comparison GOLD2 COPD vs control (b) and GOLD3/4 COPD vs control patients (c). Heatmap of the mean expression of the 20 most variable genes filtered by the GO term fatty acid metabolism (d) and fatty acid catabolic process (e).

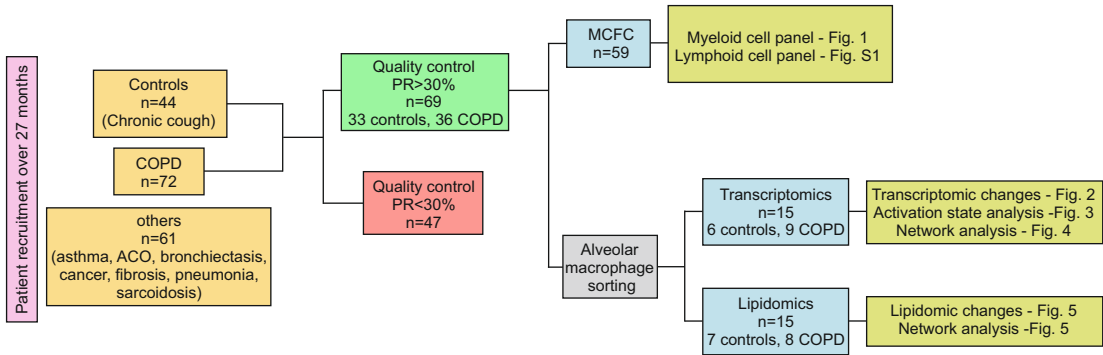
Fig. 4 – Co-expression network analysis uncovers lipid metabolism-associated functions for AMs in COPD. Schematic representation of the bioinformatics workflow for co-expression network analysis of the 6,000 most variable genes in the dataset by CoCena² (a). CoCena² cluster-condition heatmap (b). Significant enrichment (q -value < 0.1) of hallmark genes within patient groups. Patient group modules consist of the respective cluster-condition heatmap modules (c). CoCena² network with GOLD2-associated genes within the hallmark term “Cholesterol homeostasis” marked by black edging and coloured according to their cluster name. Each node represents one gene in the network and each edge represents a co-expression. The expression levels are presented in more detail in the following heatmap (d). CoCena² network with GOLD3/4-associated genes within the hallmark term “Interferon alpha response” marked by black edging and coloured according to their cluster name. Each node

represents one gene in the network and each edge represents a co-expression. The expression levels are presented in more detail in the following heatmap (e). Genes enriched within the hallmark term “G2M checkpoint” marked by black edging and coloured according to their cluster name. Each node represents one gene in the network and each edge represents a co-expression. The expression levels are presented in more detail in the following heatmap (f).

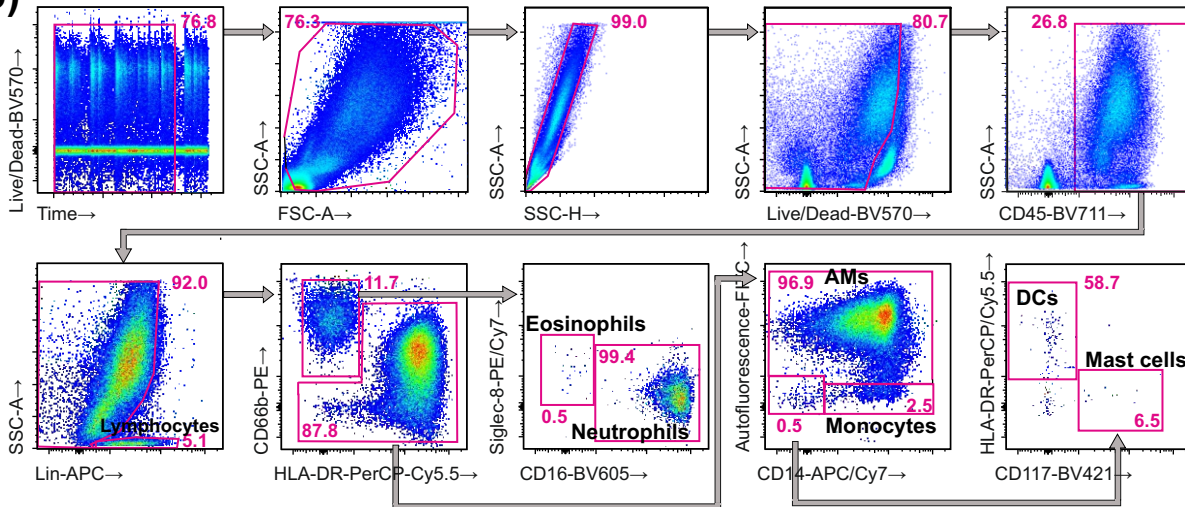
Fig. 5 – Quantitative lipidomics of AMs of COPD patients describe disease severity. Schematic representation of the analysis workflow for analysis of the 202 lipid species assessed by lipidomics of AMs from BALF of 11 COPD and 4 control patients (a). Mean mol% per patient group for lipid class sums of lipid species normalized to total identified lipid content (b). Hierarchical clustering of average \log_2 fold changes (FC) of mol% of lipid class sums (c). Average \log_2 FC of mol% for single lipid species per lipid class for GOLD2 vs control (d) or GOLD3/4 vs control (e). Bubble size indicates p-value. CoCena² cluster-condition heatmap (f). Hierarchical clustering of the average lipid abundance for lipid species encompassed in the GOLD2-specific modules 2 and 3 (g) and GOLD3/4-specific module 8 (h). CE, cholesteryl ester; Cer, ceramide; CL, cardiolipin; DAG, diacylglycerol; DiHexCer, dihexosylceramide; HexCer, hexosylceramide; LPC-O, ether-lysophosphatidylcholine; LPC, lysophosphatidylcholine; MAG, monoacylglycerol; PC-O, ether-phosphatidylcholine; PC, phosphatidylcholine; PE-O, ether-phosphatidylethanolamine; PE, phosphatidylethanolamine; PI, phosphatidylinositol

Figure 1

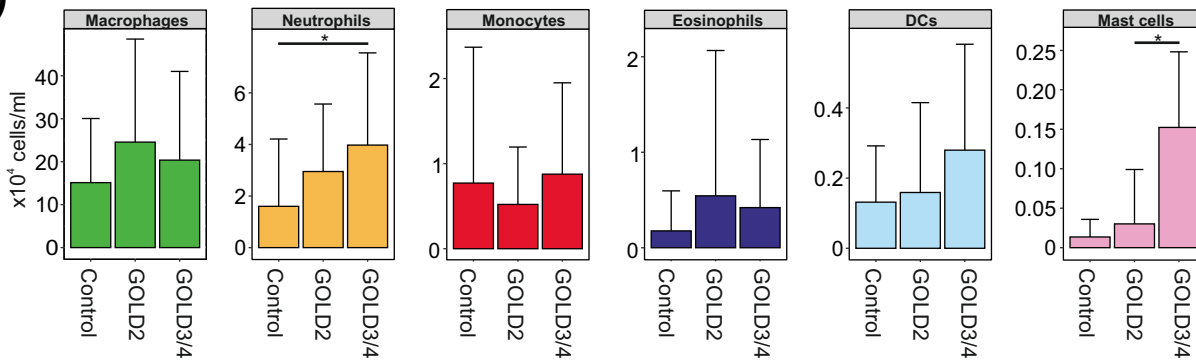
a)



b)



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d)

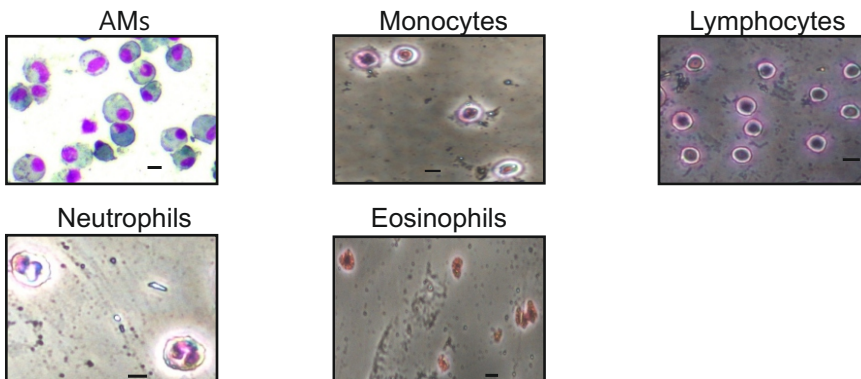


Figure 2

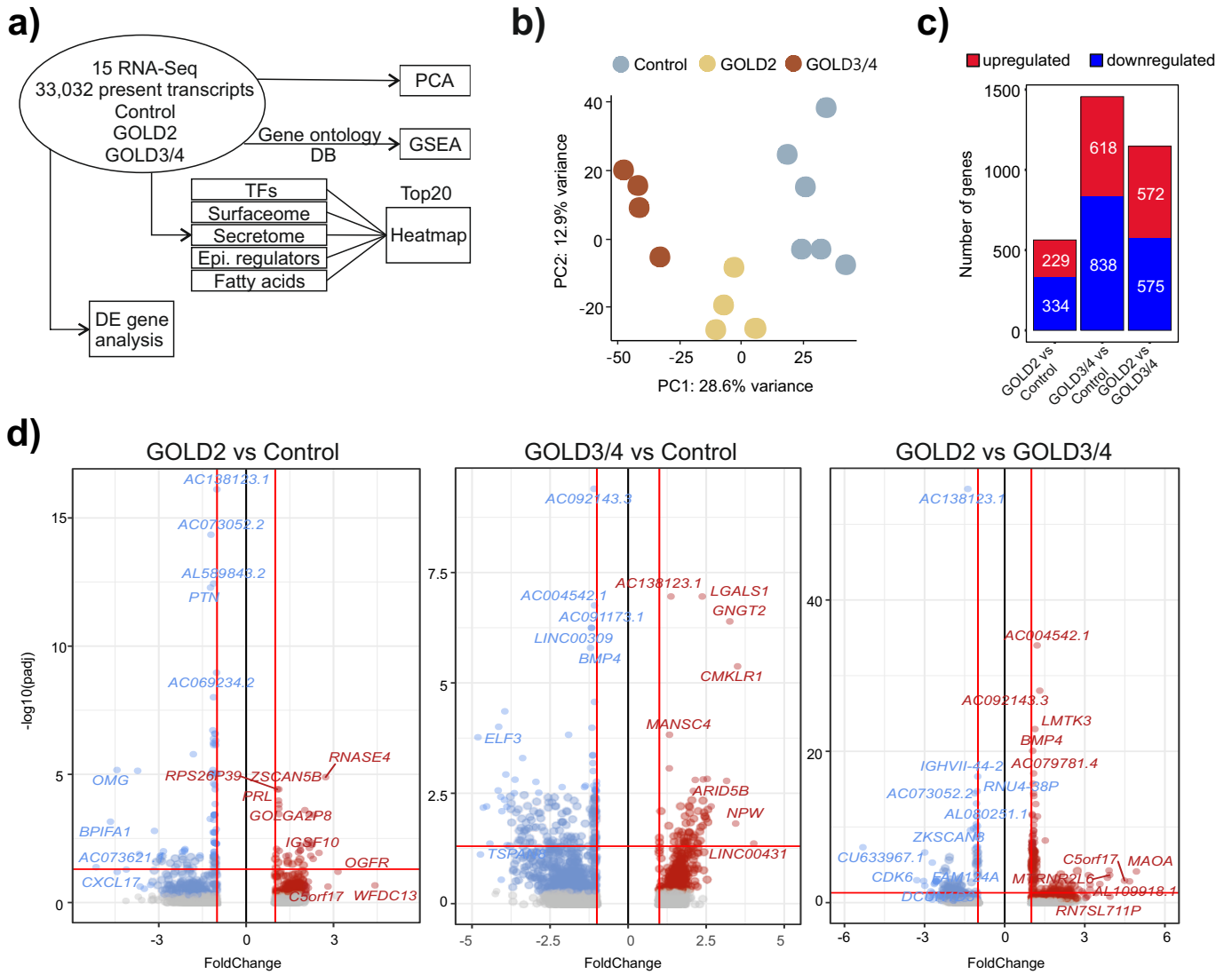


Figure 3

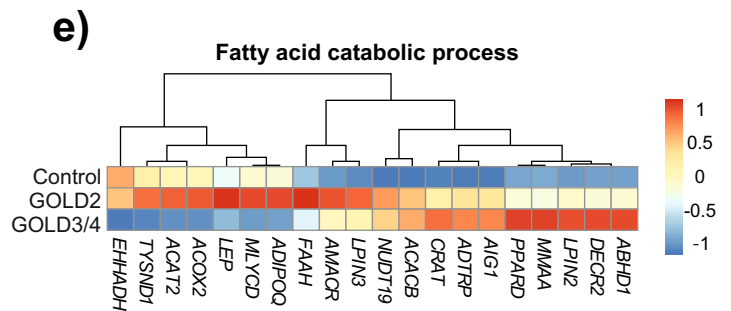
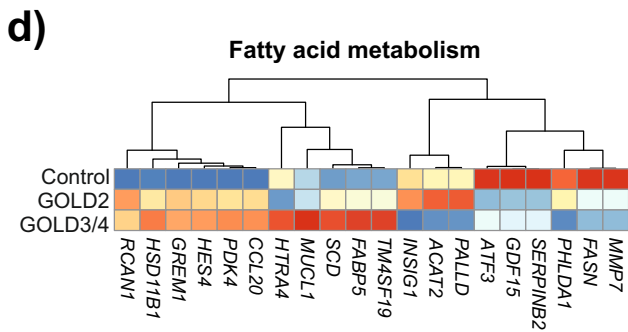
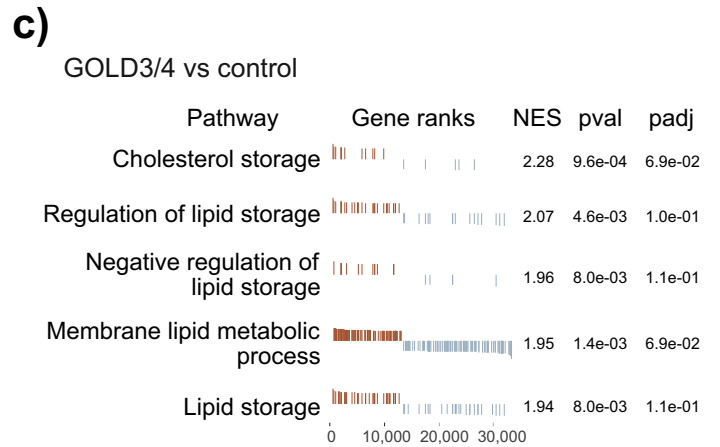
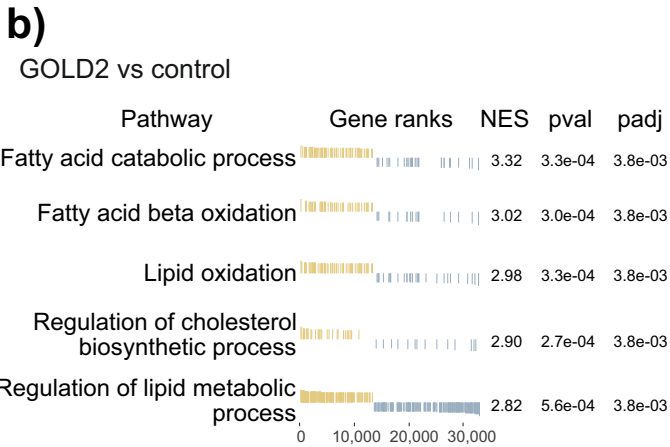
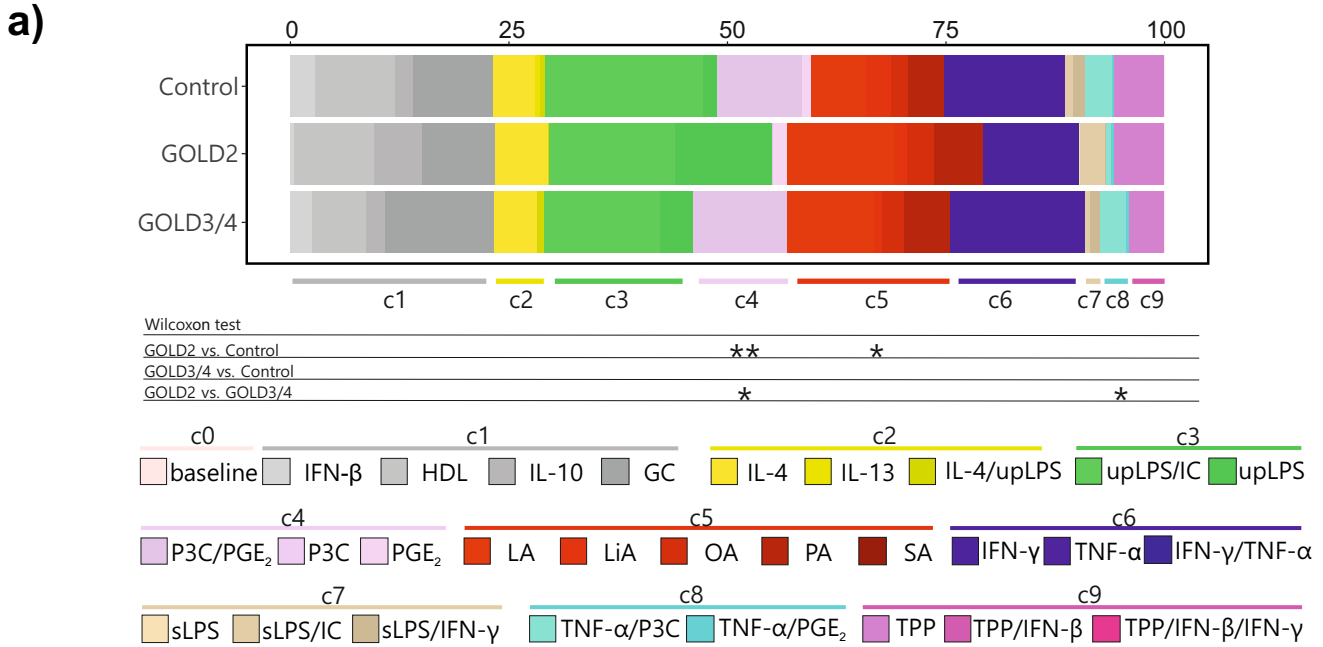
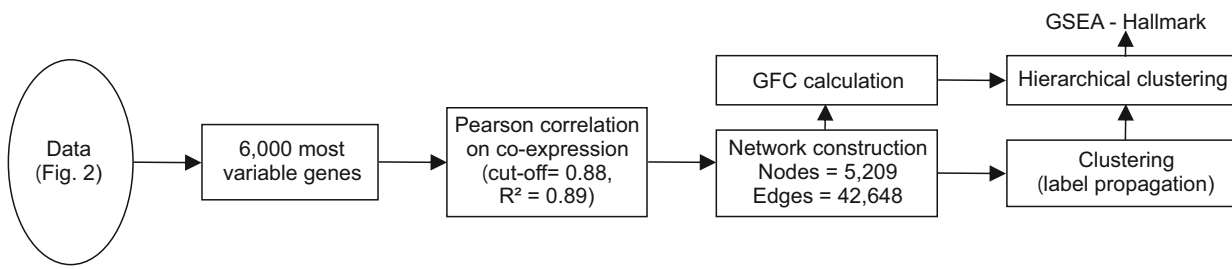
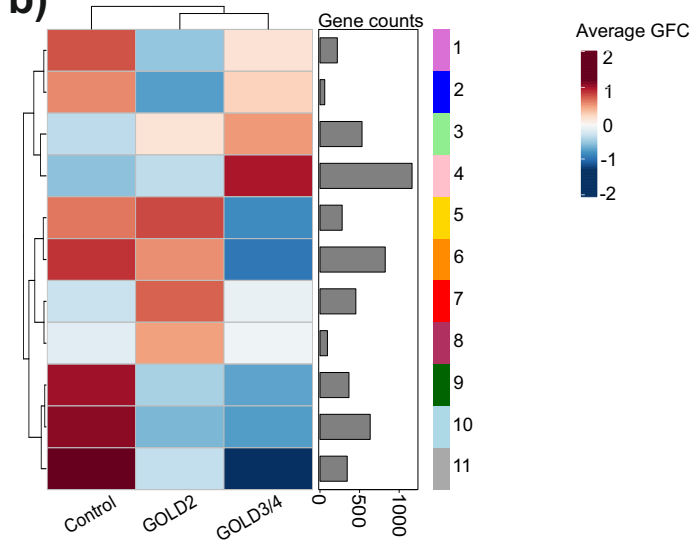


Figure 4

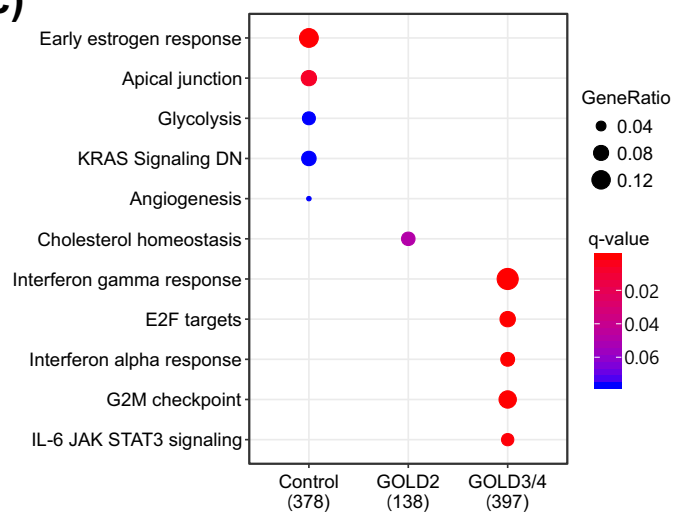
a)



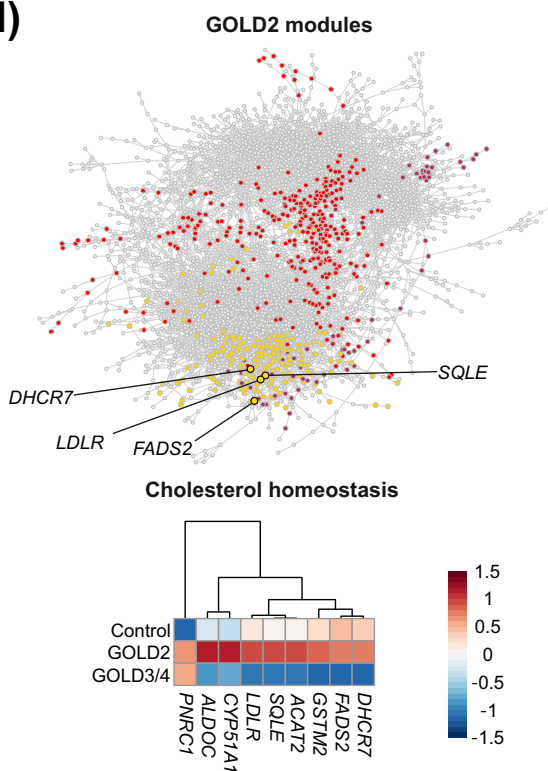
b)



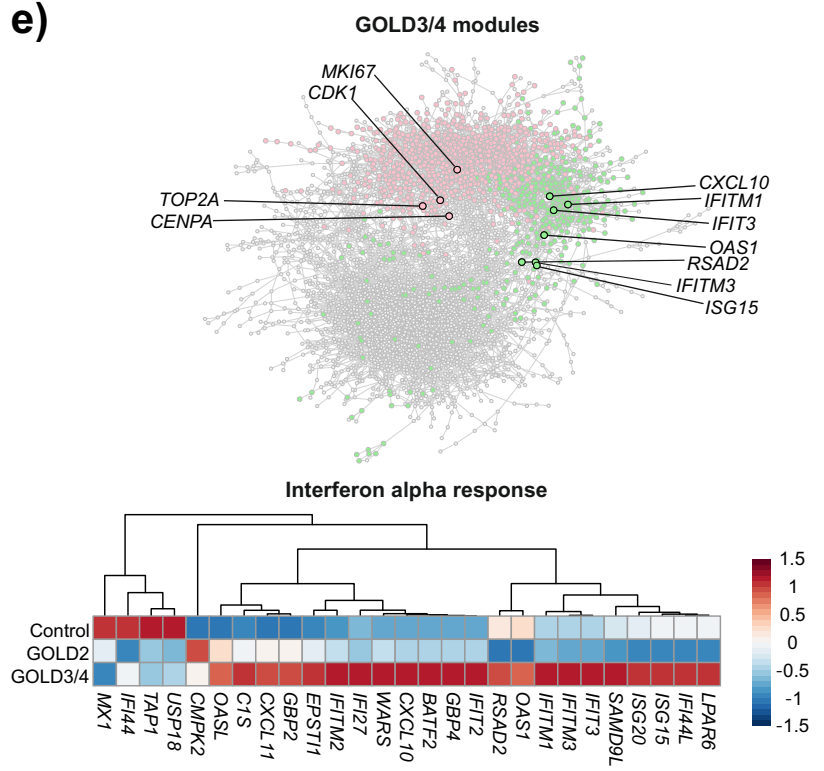
c)



d)



e)



f)

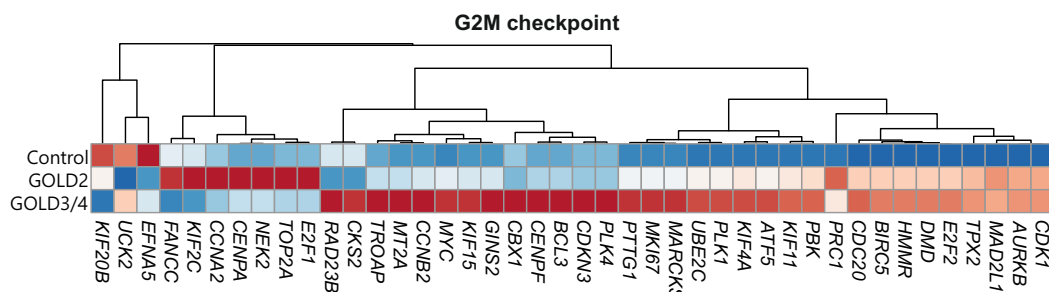
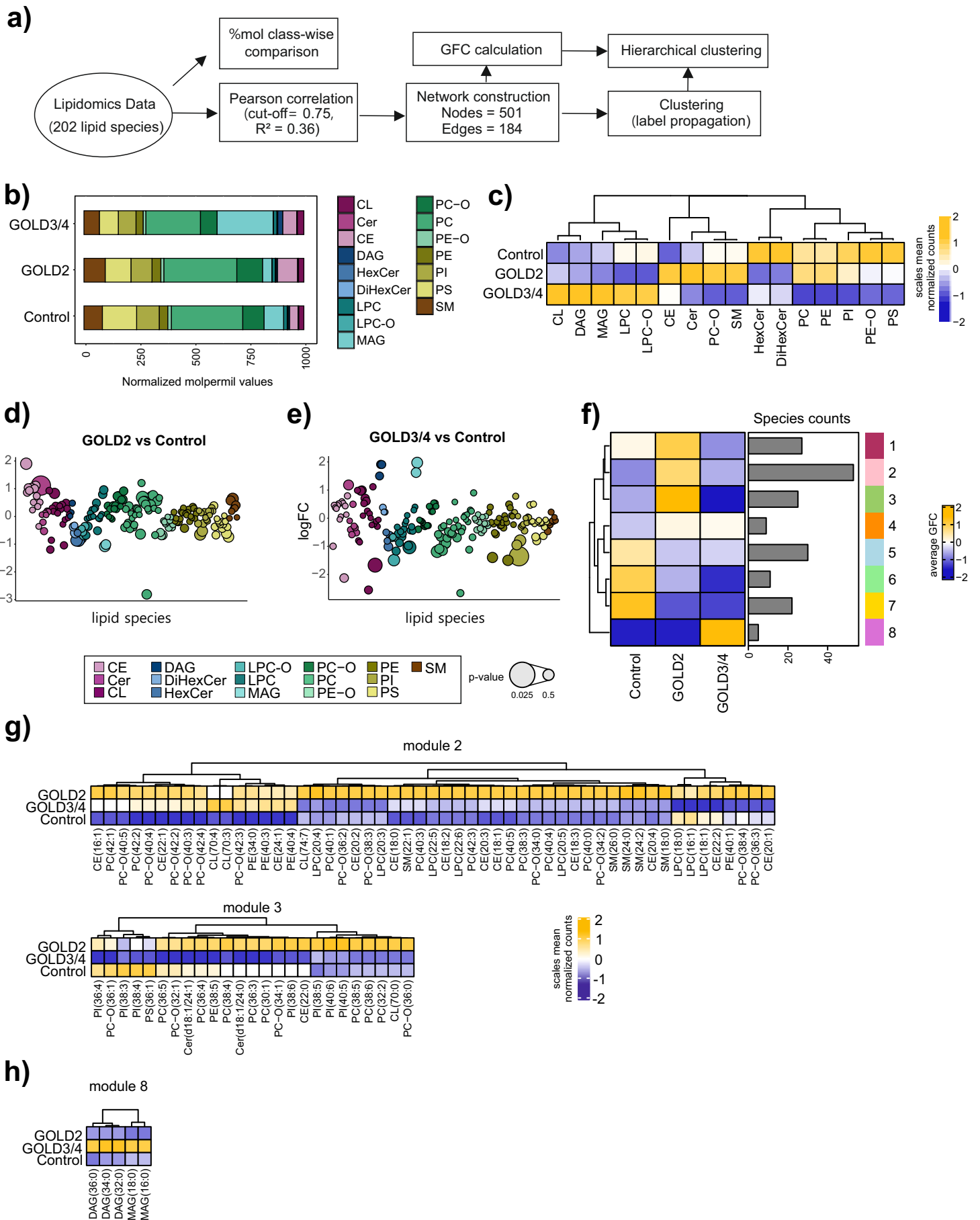


Figure 5



Alveolar macrophage transcriptomic profiling in COPD shows major lipid metabolism changes

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ONLINE DATA SUPPLEMENT

METHODS

Human specimens

Human studies were approved by the ethics committees of the University of Bonn and University hospital Bonn (local ethics vote 076/16). All patients provided written informed consent according to the Declaration of Helsinki before specimens were collected. They were recruited as part of an exploratory observational clinical cohort study consecutively over a period of 27 months from the Department of Pneumology. Patients were categorized as either control (see definition below), COPD, or other diseases (see also Fig. 1A). Patients with COPD were diagnosed and stratified according to the guidelines of the global initiative for chronic obstructive lung disease (GOLD) [1]. Eligible patients were aged 18 years or older and were either current, past or non-smokers (Table E1). Current smokers had smoked in the last 3 months, ex-smokers had not smoked in the last 3 months prior the bronchoscopy and never smokers had not smoked more than 100 cigarettes in their lifetime and did not smoke at the time of recruitment. Age-matched individuals suffering from chronic idiopathic cough, demonstrating an exquisitely sensitive cough reflex without underlying pathology [2], served as control donors. A diagnostic algorithm that considered medical history (including drugs, e.g. ACE inhibitor and indications of heart burn), physical examination, echocardiography, chest X-ray, lung function, including methacholine challenge, presentation at an HNO doctor, blood test (including exclusion of eosinophilia), FeNO (excluding >50 ppb), computer tomography of the chest and finally bronchoscopy [3] was worked up to enroll the control group. Exclusion criteria included hypoxemia despite oxygen supplementation (O_2 saturation <90%), hypercapnia, increased risk of bleeding, unstable cardiac disease, and COPD exacerbations within

the 4 weeks prior to recruitment. Patients with other pulmonary diseases (termed other (Fig. 1A)) were diagnosed as asthma, ACO, bronchiectasis, cancer, fibrosis, pneumonia and sarcoidosis (Table E2), but were excluded from further evaluation within this study.

Bronchoscopy procedure

Bronchoscopy was performed as a part of the diagnostic workup by two bronchoscopists through oral access and with light conscious sedation. All participants received supplemental oxygen by nasal cannula. After a general inspection, BAL was performed in the middle lobe or, if not accessible, the lingular lobe. Warmed saline (6 syringes of 20 ml each) was instilled into the airways to enable BALF recovery. After each instillation, the aliquot was immediately recovered by gentle hand suction into a syringe.

BALF processing

Human BALF was obtained from all patients included in the study (control, COPD, other) through bronchoscopy. Within this report, only BALF samples of the highest quality following quality criteria established previously for the processing of BALF [4], such as recovery rate higher than 30% and absence or minimal blood/mucus contamination, from control and COPD patients were used further. BALF specimens were washed with PBS, suspended with 0.02% EDTA-2Na and washed again for final re-suspension with 2% FCS/1 mM EDTA. CD45⁺Lin⁻HLA-DR⁺CD66⁻Autofluorescence⁺ AMs were sorted using a FACS Aria III cell sorter (BD Biosciences, USA).

Cell counting and decision making

Total cell counts were determined with (1:5) Trypan Blue exclusion (Sigma-Aldrich) under an optical microscope. BALF cells (10ul) were diluted 1:10 in the Trypan Blue solution and counted in a Neubauer haemocytometer. Due to material limitations, we prioritized flow cytometry-based immunophenotyping of total CD45⁺ cells. If sufficient material was available, we also sorted alveolar macrophages from the remaining cells for RNA sequencing and lipidomics. For some patients, the absolute numbers of alveolar macrophages were not sufficient for both approaches (transcriptomics and lipidomics) and we therefore proceeded to either RNA sequencing or lipidomics (Table E3).

Flow cytometry/FACS

Single-cell suspensions were stained with Live/Dead yellow fluorescent dye (ThermoFisher, USA) for 15 min at room temperature and were washed with PBS at 300xg for 5 min at 4°C. They were then re-suspended in 100 ul PBS and blocked with 5 ul human FcR blocking reagent (Miltenyi, Germany) for 15 min on ice and were subsequently stained with the listed anti-human antibodies (Table E4) in buffer containing PBS, 2% FCS, 1 mM EDTA for 30 min on ice. After an initial interim analysis of the first 36 samples, we identified a non-annotated cell population, which we identified as FcεRI⁺ mast cells. All further samples from control and COPD patients (n=23) were also interrogated for the presence of mast cells in the BALF. Cells were spun at 300xg for 5 min at 4°C and re-suspended in buffer containing PBS, 2% FCS, 1 mM EDTA for analysis. Data acquisition was performed on a FACS Aria III cell sorter

(BD Biosciences, USA). Analysis was performed with FlowJo v.10 software (Tree Star, USA).

Cytospin preparation

Cytospins were obtained by centrifuging 2×10^5 cells in 200 μ l PBS on microscope slides at 20% power for 5 min. Excess buffer was carefully discarded and slides were air dried for 3 min followed by fixation with 100% methanol for 5 min at 4°C. The slides were subsequently washed with PBS and stained with 1:20 Giemsa solution (Sigma, USA) for 25 min at room temperature. A final rinsing step with H₂O and air drying before mounting followed. Cell morphology was examined by microscopic evaluation of stained cells using an Axio Lab A1 microscope (Zeiss, Germany).

RNA extraction and library preparation

Total RNA was isolated from human AMs with the miRNeasy Micro kit (Qiagen, Germany) according to the manufacturer's protocol and RNA concentration and integrity was determined using the High Sensitivity RNA assay on a TapeStation 4200 system (Agilent, USA). All samples had RIN > 7 and therefore no exclusions were made for poor RNA quality. cDNA libraries were prepared from 5 ng total RNA with the SMART-seq2 protocol [5] and were tagged with the Nextera XT kit (Illumina, USA). Library size selection was carried out with AMPure beads (Beckman-Coulter, USA) and library size distribution was measured with the High Sensitivity D5000 assay on a TapeStation 4200 System (Agilent, USA). Library concentration was determined using the HS dsDNA assay on a Qubit. Libraries were sequenced for SR 75 cycles on a NextSeq500 system

(Illumina) using High Output v2 chemistry. Base call files were converted to fastq format and demultiplexed using bcl2fastq v2.20.

Data pre-processing and RNA sequencing analysis

The 75 bp single-end reads were aligned to the human reference transcriptome hg38 from UCSC by kallisto v0.44.0 using default parameters. Data were imported into DESeq2 (v.1.10.1; [6]) using the TXimport (v1.2.0, [7]) package. DESeq2 was used for the calculation of normalized counts for each transcript using default parameters. All normalized transcripts with a maximum over all group means lower than 10 were excluded resulting in 33,032 present transcripts. Unwanted or hidden sources of variation, such as batch, sex and smoking status were removed using the sva package [8]. Briefly, the SVA package models the provided gene expression tables to identify and construct surrogate variables which adjust for technical artifacts (batches), as well as variation of unknown sources. Subsequently, the user can assess these variables and test how each of the undesired factors is corrected by the algorithm. The normalized rlog transformed expression values were adjusted according to the five surrogate variables identified by sva using the function removeBatchEffect from the limma package [9]. DE genes were defined by a p-value cut-off of 0.05 and an adjusted p-value (IHW) < 0.5 (independent hypothesis weighting). All present transcripts were used as input for principal component analysis. Pearson Correlation Coefficient Matrix (PCCM) and the top 25% most variable transcripts within the dataset were selected and visualized as heatmaps.

Gene set enrichment analysis (GSEA)

To test for functional enrichment between COPD (GOLD2 and GOLD3/4, respectively) and control patients, we performed GSEA [10] on all present genes of the dataset using the gene ontology set of biological processes. Information of gene ontology was obtained from the biological process gene set “c5.bp.v7.0.symbols.gmt”, downloaded from the Molecular Signatures Database (MSigDB). All present genes were used as background (universe). Lipid-related genes were extracted upon filtering gene ontology terms for the keywords “fat” and “lipid”. Data were FDR-corrected.

Linear support vector regression

Linear support vector regression [11] was employed to characterize the relative contribution of 28 different activation signatures derived from [12] to the control and COPD patients. Our normalized gene expression table was utilized as input mixture file and the published activation signatures in [12] were used to compute the relative activation signatures within bulk control and COPD samples (1,000 permutations). The union of the c5 module genes (Fig. 3A) was used as a fatty acid signature and the 20 most variable genes were visualized in a heatmap.

Filtering for TFs, epigenome, surfaceome and secretome

All present transcripts were filtered and sorted by their variance in the dataset. The 20 most variable genes of each category were selected and visualized in heatmaps. TF lists were extracted from [13], the epigenome gene list was derived from the literature, surface and secretome markers were extracted from the Human Protein Atlas [14, 15].

Construction of co-expressed network analysis – automated (CoCena²)

To elucidate similarities and differences within the gene expression patterns of the three different patient groups -control, GOLD2 and GOLD3/4 COPD- CoCena² was performed. Pearson correlation was calculated on the 6,000 most variable genes within the dataset using the R package Hmisc (v4.3-0; [16]). Data were filtered for significant (p-value < 0.05, Bonferroni correction p<0.05) and positive (r-value > 0) correlation values. A Pearson correlation coefficient cutoff of 0.88 was applied as this yields a scale-free network ($R^2 = 0.89$) with 5,209 nodes and 42,648 edges. The Group Fold Change (GFC) was calculated for each gene and each condition on the inverse logarithmic count data using the R package gtools (v3.8.2; [17]). In brief, the mean expression of each gene for each patient group versus the overall mean expression of the gene was calculated. Unbiased clustering was performed using the R package igraph (v1.2.4.1; [18]). Five different clustering algorithms, namely “cluster_label_prop”, “cluster_fast_greedy”, “cluster_louvain”, “cluster_infomap” and “cluster_walktrep”, were tested and “cluster_louvain” was selected as it achieves the highest modularity score. The mean GFC for each cluster and condition was visualized in the cluster-condition heatmap using the R package ComplexHeatmap (v2.0.0; [19]). Clusters with less than 35 genes are not shown. Hierarchical clustering was performed on genes and cluster modules using the Euclidean clustering distance and the complete-linkage clustering method. Network generation was performed with the R package igraph. The network information was imported to and exported from Cytoscape using the R package RCy3 (v2.6.2; [20]). In Cytoscape, the prefuse force-directed layout was applied to the network. Network visualization was performed using the R packages ggnetwork (v0.5.1,

[21]) and ggplot2 (v3.2.1; [22]).

Biological function-related bioinformatic analysis of network modules

GSEA was performed on the patient group-related modules identified by CoCena² using the R package ClusterProfiler (v3.12.0; [23]). The *compareCluster* function was used to determine significant enrichment (q-value < 0.1 using the Benjamini-Hochberg method) of hallmark gene sets of biological processes. Information of hallmark genes was obtained from the hallmark gene set “h.all.v6.1.symbols.gmt”, downloaded from the Molecular Signatures Database (MSigDB). All genes present in the network were used as background (universe). Interesting hallmark terms for each patient group were selected and the mean gene expression of all genes within the selected term was visualized in heatmaps using the R package pheatmap (v1.0.12; [24]). The gene expression values were scaled over the three groups. Hierarchical clustering was performed on the genes using the Euclidean clustering distance and the complete clustering method. Enriched genes were highlighted on the CoCena² network.

Lipidomics

Sorted AMs (5×10^4) were washed with PBS, suspended with 150 mM ammonium acetate (Merck, Germany) and transferred into a glass tube. After centrifugation at 300xg for 10 min with low brake, supernatants were discarded, and the pellets were frozen at -80°C until analysis. Extraction mix (Chloroform 1:5 methanol-containing internal standards: 210 pmol PE(31:1), 396 pmol PC(31:1), 98 pmol PS(31:1), 84 pmol PI(34:0) , 56 pmol PA(31:1), 51 pmol PG (28:0), 28 pmol CL(56:0), 39 pmol LPA (17:0),

35 pmol LPC(17:1), 38 pmol LPE (17:1), 32 pmol Cer(17:0), 99 pmol SM(17:0), 55 pmol GlcCer(12:0), 14 pmol GM3 (18:0-D3), 359 pmol TG(47:1), 111 pmol CE(17:1), 64 pmol DG(31:1), 103 pmol MG(17:1), 724 pmol Chol(d6), 45 pmol Car(15:0)) was spiked to the pellets before 2 min sonication and centrifugation at 20,000xg for 2 min. Chloroform and 1% acetic acid were added and the samples were spun at 20,000xg for 2 min. The lower phase was transferred and let evaporate in the vacuum concentrator (45°C for 10 min). Spray buffer (8/5/1 2-propanol/methanol/water, 10 mM ammonium acetate) was added, the samples were sonicated for 5 min and analyzed separately by infusing them at 10 ul/min into a Thermo Q Exactive Plus spectrometer equipped with the HESI II ion source for shotgun lipidomics. MS1 spectra (res. 280,000) were recorded in 100 m/z windows from 200 – 1,200 m/z (pos.) and 200 – 1,700 m/z (neg.) followed by recording of MS/MS spectra (res. 70,000) by data independent acquisition in 1 m/z windows from 200 – 1,200 (pos.) and 200 – 1,700 (neg.) m/z.

Lipidomics analysis

Raw files were converted to .mzml format and imported into the LipidXplorer software for analysis using custom mfql files to identify sample lipids and internal standards. Raw data were filtered during import into LipidXplorer by global thresholding in MS1 and MS2 to remove small stochastic noise peaks. For identification, mass errors were limited to 6 ppm in MS1 and 0.005 Th in MS2. The average mass error over all identifications in MS1 was 1.76 ppm. For a valid identification, all species must show both an identification of the unfragmented peak in MS1 and at least one specific fragment in MS2. Consistency of analysis was checked by determination of the coefficient of

variation of the intensities of the spiked internal standards within one sample series and was found to be 11.7%. Despite the low number of cells, total identified lipids in samples were 5.5-15-fold over the background blank. Further, species pattern within lipid classes were checked for consistency with expectations. We found the very characteristic pattern of dominating saturated PC (but not PC-O) and saturated DAG species (32:0, 34:0) characteristic for the lung tissue, originating from lung surfactant secretion. PE and PI showed the expected dominating PUFA-containing PE(38:4) and PI(38:4). The pattern of CE showed a stronger signal for CE(18:1) than CE(18:2), ruling out major contamination with blood, in which CE(18:2) is about 3-fold more abundant than CE(18:1). Lipid species showing signals above the blank in min. 70% of the samples were included in the analysis. For further data processing, absolute amounts were calculated using the internal standard intensities followed by normalization on the sum of all measured lipid species per sample. %mol values were averaged for each patient group, log₂-transformed and then used for fold change calculations. To find patient group-specific co-regulated lipid species, CoCena² was used as for the transcriptome analysis. Pearson correlation was calculated on all lipid species. Data were filtered for significant (p -value < 0.05, Bonferroni correction $p < 0.05$) and positive (r -value > 0) correlation values leading to the construction of a correlation network with 501 nodes and 184 edges (Pearson correlation coefficient cut-off of 0.75). The GFC was calculated for each lipid species and each condition and clustering performed using the “cluster_louvain” algorithm. Mean GFCs for each cluster and condition are visualized in the cluster-condition heatmap. Hierarchical clustering was performed on lipid species and cluster modules using the Euclidean clustering distance and the complete-linkage

clustering method. Network generation was performed with the R package igraph.

Statistics

A two-tailed Welch's unpaired t test was used to analyze data from two groups. Equality of population variance was assessed with the F-test statistic for two independent groups. A non-parametric Wilcoxon test was used to perform a pairwise comparison between patient groups for all enriched macrophage activation signatures in Fig. 3F. For more than two groups, normality and homoscedasticity were first assessed using the Shapiro-Wilk and Levene tests in R (v3.6.1). A non-parametrical Kruskal-Wallis test with Dunn's multiple correction post hoc was used in Fig. E3 because the data did not follow a normal distribution. Statistical significance was inferred when $p < 0.05$.

Data and code availability

The transcriptomic data are deposited at the European Genome-phenome Archive (EGA), which is hosted by the EBI and the CRG, under accession number EGAS00001004244. Flow cytometry files can be found at www.flowrepository.org under FR-FCM-Z2JL. Lipidomic data and annotation are provided in Tables E6 and E7. The code for CoCena² is publicly deposited on GitHub (<https://github.com/UlasThomas/CoCena2>).

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SUPPLEMENTARY FIGURES

Fig. S1 – Representative multi-color flow cytometry analysis of the lymphoid compartment of a control patient (a). Absolute numbers of lymphoid immune cells in the BALF of control, GOLD2 and GOLD3/4 COPD patients calculated with traditional gating. Data are from 8-23 patients per group and are represented as mean \pm SD (b). Bar plot of ILC concentration in BALF of control and COPD patients calculated with flow cytometry traditional gating (c). Bar plot of ILC1 concentration in the BALF of control and COPD patients calculated with flow cytometry traditional gating (d). Mean \pm SD is shown from 16-17 patients and data were analysed with an unpaired two-tailed student t-test, * $p < 0.05$, BALF, bronchoalveolar lavage fluid; ILC, innate lymphoid cell

Fig. S2 - Hierarchical clustering of the 25% most variable transcripts (a). Matrix of hierarchically clustered PCCM showing the distance from 0 to 100 (blue to red) based on all present transcripts (b). Hierarchical clustering of the patient group means of the top 20 most variable transcripts filtered by a list of TFs (c), known epigenetic regulators (d), surface (e) and secreted molecules (f), PCCM, Pearson correlation coefficient matrix; TF, transcription factor

SUPPLEMENTARY TABLES

Table 1 – Detailed demographics of control and COPD patients.

Table 2 – Detailed demographics of rejected patients.

Table 4 – Detailed information for the antibodies used in the study.

Table 5 – Surface markers that were used to identify major immune cell types in BALF from control and COPD patients.

Table 6 – Raw lipidomic data generated in the study.

Table 7 - Lipidomic data annotation table.

Table E1

Patient ID	Diagnosis	BALF volume recovered	BALF recovery ratio	Cellularity (millions)	FEV1/FVC	FEV1% GOLD grade	Group	Sex	Age	Smoking history	Packyears	LAMA	LABA	ICS	Death	Hospitalizations/year	Exacerbations/year	Flow cytometry	RNA-seq	Lipidomics	
12	Chronic cough	65	0.54	5.3	72	90	NA	M	61	Past	20	No	Formoterol 6 ug	Beclomastax 100 ug	No	0	0	Yes	No	No	
18	Chronic cough	40	0.33	5.6	86	77	NA	F	56	Never	NA	Tiotropium 2.5 ug	Clodaterol 2.5 ug	No	0	0	Yes	No	No		
21	Chronic cough	45	0.38	20.4	85	109	NA	F	36	Never	NA	No	No	No	0	0	0	Yes	No	No	
22	Chronic cough	35	0.29	9.8	82	101	NA	F	68	Never	NA	No	No	No	0	0	0	Yes	No	No	
27	Chronic cough	100	0.83	19.4	89	108	NA	M	67	Past	20	No	No	No	0	0	0	Yes	No	No	
35	Chronic cough	35	0.29	2.3	109	82	NA	M	65	Current	75	No	No	No	0	0	0	Yes	No	No	
36	Chronic cough	65	0.54	1.3	82	95	NA	F	49	Past	2	No	No	No	0	0	0	Yes	No	No	
39	Chronic cough	35	0.29	4.2	75	90	NA	M	59	Current	45	No	No	No	0	0	0	Yes	No	No	
45	Chronic cough	45	0.38	3.3	107	102	NA	F	62	Current	30	No	No	No	0	0	0	Yes	No	No	
51	Chronic cough	35	0.29	5.2	111	100	NA	F	68	Never	NA	No	No	No	0	0	0	Yes	No	No	
56	Chronic cough	45	0.38	1.1	91	101	NA	F	58	Never	NA	No	No	No	0	0	0	Yes	No	No	
59	Chronic cough	50	0.42	0.5	89	88	NA	F	30	Past	2	No	No	No	0	0	0	Yes	No	Yes	
61	Chronic cough	55	0.46	1.4	84	80	NA	F	60	Never	NA	No	No	No	0	0	0	Yes	No	No	
72	Chronic cough	40	0.33	0.5	91	101	NA	F	74	Never	NA	No	No	No	0	0	0	Yes	No	No	
74	Chronic cough	50	0.42	4	111	92	NA	M	44	Past	15	No	No	No	0	0	0	Yes	No	No	
77	Chronic cough	30	0.25	5.6	90	89	NA	F	58	Never	NA	No	No	No	0	0	0	Yes	No	Yes	
79	Chronic cough	40	0.33	21	102	102	NA	F	56	Never	NA	No	No	No	0	0	0	Yes	No	No	
91	Chronic cough	35	0.29	31	85	70	NA	M	41	Never	NA	No	No	No	0	0	0	No	Yes	No	
111	Chronic cough	45	0.38	21	78	92	NA	F	27	Never	NA	No	No	No	0	0	0	Yes	No	Yes	
113	Chronic cough	65	0.54	20.5	84	99	NA	M	65	Never	NA	No	No	No	0	0	0	Yes	Yes	Yes	
116	Chronic cough	45	0.38	25	76	96	NA	M	58	Past	25	No	No	No	0	0	0	Yes	No	Yes	
123	Chronic cough	50	0.42	13.9	77	96	NA	F	53	Past	40	Glycopyrronium 85 ug	Indacaterol 43 ug	Budesonid 400 ug	No	0	0	Yes	No	No	
128	Chronic cough	50	0.42	1.69	78	69	NA	F	53	Never	NA	No	No	No	0	0	0	Yes	No	No	
133	Chronic cough	40	0.33	4.8	80	111	NA	F	49	Never	NA	No	No	No	0	0	0	Yes	No	No	
135	Chronic cough	60	0.50	18.1	77	132	NA	M	56	Never	NA	No	No	No	0	0	0	Yes	No	Yes	
139	Chronic cough	50	0.42	10.5	78	88	NA	F	55	Never	NA	No	No	No	0	0	0	Yes	No	No	
141	Chronic cough	60	0.50	4.5	76	97	NA	M	60	Never	NA	No	No	No	0	0	0	Yes	No	Yes	
146	Chronic cough	80	0.67	6.3	86	89	NA	F	45	Never	NA	No	No	No	0	0	0	Yes	No	No	
167	Chronic cough	35	0.29	7.8	105	78	NA	M	52	Current	30	Tiotropium 10 ug	No	No	0	0	0	Yes	No	No	
172	Chronic cough	50	0.42	22.1	78	110	NA	M	53	Never	NA	No	No	No	0	0	0	Yes	No	Yes	
177	Chronic cough	45	0.38	10.5	79	63	NA	F	62	Current	40	No	Formoterol 9 ug	Budesonid 320 ug	No	0	0	Yes	No	No	
184	Chronic cough	70	0.58	4.2	86	99	NA	M	48	Past	1	No	No	No	0	0	0	No	Yes	No	
190	Chronic cough	40	0.33	46.2	76	117	NA	M	60	Past	8	No	No	No	0	0	0	No	Yes	No	
1	COPD	40	0.33	3.1	67	40	3	D	M	63	Past	150	Spiriva 18 ug	Formoterol 9 ug	Budesonid 320 ug	No	1	2	Yes	No	No
1	COPD	80	0.67	7.1	65	42	4	D	M	63	Past	150	Spiriva 18 ug	Formoterol 9 ug	Budesonid 320 ug	No	1	2	Yes	No	No
16	COPD	40	0.33	5.2	66	64	2	B	M	71	Current	27	Tiotropium 2.5 ug	Clodaterol 2.5 ug	No	NA	NA	Yes	No	No	
32	COPD	60	0.50	8.1	67	26	4	D	M	64	Past	150	Spiriva 18 ug	Formoterol 9 ug	Budesonid 320 ug	No	1	2	Yes	No	No
40	COPD	45	0.38	8.2	59	45	3	B	F	80	Past	35	Umeclidinium 65 ug	No	3	Yes	3	Yes	No	No	
44	COPD	40	0.33	6.8	48	56	2	B	M	74	Past	40	No	No	Yes	0	0	Yes	No	No	
47	COPD	40	0.33	7.8	55	41	3	B	M	67	Past	80	Glycopyrronium 43 ug	Indacaterol 85 ug	No	0	2	Yes	No	No	
48	COPD	35	0.29	9.4	55	48	3	B	F	81	Past	25	No	No	No	0	0	Yes	No	No	
52	COPD	60	0.50	4	52	46	3	B	F	81	Past	25	No	No	No	0	0	Yes	No	No	
54	COPD	60	0.50	24.3	61	38	3	D	M	72	Past	50	Glycopyrronium 50 ug	Indacaterol 110 ug	No	0	1	Yes	No	No	
80	COPD	50	0.42	6	44	32	3	D	F	59	Past	50	Tiotropium 2.5 ug	Clodaterol 2.5 ug	No	0	0	Yes	No	Yes	
83	COPD	50	0.42	31	68	79	2	B	M	64	Past	135	Tiotropium 2.5 ug	Formoterol 6 ug	Beclomastax 200 ug	No	1	2	Yes	Yes	Yes
94	COPD	40	0.33	1.35	62	60	2	D	F	57	Current	40	Tiotropium 2.5 ug	Clodaterol 2.5 ug	No	0	1	Yes	No	No	
103	COPD	50	0.42	10.2	67	47	3	D	F	64	Past	62	Tiotropium 2.5 ug	Clodaterol 2.5 ug	No	0	1	Yes	No	Yes	
105	COPD	50	0.42	32	66	34	3	B	M	60	Current	35	Tiotropium 2.5 ug	Clodaterol 2.5 ug	No	0	0	Yes	No	Yes	
115	COPD	50	0.42	24	69	69	2	B	M	80	Past	10	No	No	No	1	1	Yes	No	No	
120	COPD	40	0.33	8.4	69	68	2	B	M	62	Never	NA	No	No	No	0	0	No	Yes	No	
122	COPD	40	0.33	6.9	69	64	2	B	M	48	Current	30	Tiotropium 2.5 ug	Clodaterol 2.5 ug	No	0	0	No	Yes	No	
130	COPD	35	0.29	6.8	69	67	2	B	M	68	Past	60	No	No	No	1	2	Yes	No	No	
137	COPD	45	0.38	5.2	65	68	2	D	M	59	Past	70	Tiotropium 2.5 ug	Clodaterol 2.5 ug	No	0	0	Yes	No	Yes	
142	COPD	65	0.54	11	68	63	2	B	M	68	Past	20	Tiotropium 18 ug	Salmeterol 50 ug	Fluticason 100 ug	No	0	0	Yes	No	No
145	COPD	50	0.42	10.1	67	57	2	D	F	46	Current	40	Tiotropium 2.5 ug	Clodaterol 2.5 ug	No	0	1	Yes	No	Yes	
152	COPD	35	0.29	11.4	61	67	2	B	M	58	Current	60	Glycopyrronium 85 ug	Indacaterol 43 ug	No	0	1	Yes	No	No	
155	COPD	40	0.33	4.8	68	80	2	B	M	54	Current	100	Tiotropium 18 ug	Formoterol 6 ug	Beclomastax 100 ug	No	0	0	Yes	No	Yes
157	COPD	70	0.58	15	60	71	2	B	M	52	Past	30	Tiotropium 2.5 ug	Clodaterol 2.5 ug	No	0	0	Yes	No	No	
160	COPD	35	0.29	46	66	70	2	B	M	77	Past	45	Tiotropium 2.5 ug	Clodaterol 2.5 ug	No	0	0	Yes	No	No	
161	COPD	35	0.29	11	65	29	4	D	F	67	Past	20	Tiotropium 18 ug	Formoterol 9 ug	Budesonid 320 ug	No	0	1	Yes	No	No
162	COPD	35	0.29	10.1	55	73	2	D	F	63	Past	15	Tiotropium 2.5 ug	Formoterol 6 ug	No	0	0	Yes	No	No	
164	COPD	40	0.33	11.4	56	50	2	D	M	63	Current	50	Tiotropium 2.5 ug	Clodaterol 2.5 ug	No	1	1	Yes	No	No	
173	COPD	50	0.42	4.8	55	59	2	B	M	74	Current	50	Glycopyrronium 85 ug	Indacaterol 43 ug	No	Yes	1	1	Yes	No	No
175	COPD	40	0.33	15	66	50	2	D	M	55	Past	70	Glycopyrronium 44 ug	Formoterol 4.5 ug	Budesonid 160 ug	No	1	1	Yes	No	No
176	COPD	50	0.42	1.5	65	33	3	D	M	67	Past	60	Tiotropium 2.5 ug	Clodaterol 2.5 ug	No	1	1	Yes	No	Yes	
185	COPD	50	0.42	21.5	66	49	3	B	M	63	Current	50	Tiotropium 2.5 ug	Clodaterol 2.5 ug	No	0	2	No	Yes	No	
194	COPD	35	0.29	7.5	65	47	3	A	M	68	Current	30	No	Formoterol 6 ug	Beclomastax 100 ug	No	0	0	No	Yes	No
200	COPD	25	0.21	3.2	53	29	4	D	M	63	Current	40	Glycopyrronium 85 ug	Indacaterol 43 ug	No	0	2	No	Yes	No	
202	COPD	35	0.29	30	51	27	4	B	M	67	Past	70	Tiotropium 2.5 ug	Clodaterol 2.5 ug	No	0	2	No	Yes	No	

Table E2

Patient ID	Diagnosis	BALF volume recovered	BALF recovery ratio	Reason for rejection	Cellularity (millions)
13	ACOS	30	0.25	diagnosis	1.35
26	ACOS	15	0.13	diagnosis	4.1
28	ACOS	25	0.21	diagnosis	22.4
107	ACOS	20	0.17	diagnosis	1
132	ACOS	40	0.33	diagnosis	2
147	ACOS	40	0.33	diagnosis	3
169	ACOS	50	0.42	diagnosis	4.8
5	Asthma	15	0.13	diagnosis	not calculated
6	Asthma	10	0.08	diagnosis	not calculated
30	Asthma	35	0.29	diagnosis	11.3
33	Asthma	25	0.21	diagnosis	15.6
37	Asthma	45	0.38	diagnosis	4.2
38	Asthma	45	0.38	diagnosis	3.1
46	Asthma	40	0.33	diagnosis	4.5
58	Asthma	20	0.17	diagnosis	0.8
65	Asthma	45	0.38	diagnosis	46
96	Asthma	50	0.42	diagnosis	5.5
98	Asthma	20	0.17	diagnosis	22.3
110	Asthma	50	0.42	diagnosis	19.5
117	Asthma	50	0.42	diagnosis	0.67
124	Asthma	50	0.42	diagnosis	18
134	Asthma	45	0.38	diagnosis	11.6
150	Asthma	45	0.38	diagnosis	0.8
153	Asthma	32	0.27	diagnosis	63
171	Asthma	25	0.21	diagnosis	30
70	Atelectasis	35	0.29	diagnosis	14.8
9	Cancer	20	0.17	diagnosis	not calculated
11	Cancer	25	0.21	diagnosis	not calculated
24	Cancer	40	0.33	diagnosis	6.5
62	Cancer	75	0.63	diagnosis	2.1
81	Cancer	30	0.25	diagnosis	3.3
88	Cancer	50	0.42	diagnosis	22
73	Chronic cough	40	0.33	bloody sample	18
76	Chronic cough	42	0.35	bloody sample	13.2
90	Chronic cough	42	0.35	bloody sample	0.8
106	Chronic cough	30	0.25	bloody sample	15.8
127	Chronic cough	45	0.38	low recovery ratio (less than 30%)	3.6
138	Chronic cough	27	0.23	low recovery ratio (less than 30%)	1
2	COPD	35	0.29	low recovery ratio (less than 30%)	11.8
3	COPD	5	0.04	bronchial lavage	9.2
4	COPD	5	0.04	low recovery ratio (less than 30%)	11.6
7	COPD	10	0.08	low recovery ratio (less than 30%)	not calculated
10	COPD	5	0.04	low recovery ratio (less than 30%)	not calculated
14	COPD	25	0.21	low recovery ratio (less than 30%)	1.56
15	COPD	15	0.13	low recovery ratio (less than 30%)	not calculated
17	COPD	20	0.17	low recovery ratio (less than 30%)	1.4
20	COPD	75	0.63	bloody sample	120
23	COPD	42	0.35	bloody sample	8.4
25	COPD	15	0.13	low recovery ratio (less than 30%)	2
29	COPD	40	0.33	presence of mucus	not calculated
31	COPD	15	0.13	low recovery ratio (less than 30%)	5.6
34	COPD	20	0.17	low recovery ratio (less than 30%)	not calculated
41	COPD	15	0.13	low recovery ratio (less than 30%)	2.1
42	COPD	35	0.29	low recovery ratio (less than 30%)	26
43	COPD	30	0.25	low recovery ratio (less than 30%)	4.8
49	COPD	35	0.29	low recovery ratio (less than 30%)	not calculated
50	COPD	40	0.33	bloody sample/presence of mucus	not calculated
53	COPD	10	0.08	low recovery ratio (less than 30%)	not calculated
55	COPD	35	0.29	presence of mucus	20.4
57	COPD	25	0.21	low recovery ratio (less than 30%)	1
60	COPD	28	0.23	bloody sample	68.4
66	COPD	20	0.17	low recovery ratio (less than 30%)	not calculated
67	COPD	15	0.13	low recovery ratio (less than 30%)	not calculated
68	COPD	35	0.29	bloody sample	7
69	COPD	32	0.27	bloody sample	12.6
71	COPD	40	0.33	presence of mucus	not calculated
75	COPD	30	0.25	low recovery ratio (less than 30%)	0.7
84	COPD	35	0.29	bloody sample	21
85	COPD	45	0.38	presence of mucus	0.5
86	COPD	0	0.00	low recovery ratio (less than 30%)	not calculated
89	COPD	25	0.21	low recovery ratio (less than 30%)	0.2
92	COPD	25	0.21	low recovery ratio (less than 30%)	1
93	COPD	15	0.13	low recovery ratio (less than 30%)	1.1
95	COPD	17	0.14	bloody sample/presence of mucus	13.9
97	COPD	22	0.18	bloody sample	16.5
99	COPD	25	0.21	bloody sample/presence of mucus	13.6
100	COPD	60	0.50	bloody sample	10.2
101	COPD	30	0.25	presence of mucus	0.72
102	COPD	27	0.23	bloody	56.4
104	COPD	45	0.38	bloody sample/presence of mucus	14.4
108	COPD	20	0.17	presence of mucus	1
109	COPD	20	0.17	bloody sample	1
119	COPD	22	0.18	presence of mucus	0.2
125	COPD	40	0.33	low recovery ratio (less than 30%)	20.3
126	COPD	20	0.17	presence of mucus	0.09
129	COPD	10	0.08	low recovery ratio (less than 30%)	not calculated
136	COPD	15	0.13	low recovery ratio (less than 30%)	0.2
140	COPD	37	0.31	bloody sample	30
143	COPD	30	0.25	presence of mucus	not calculated
144	COPD	35	0.29	presence of mucus	0.3
151	COPD	12.5	0.10	low recovery ratio (less than 30%)	not calculated
154	COPD	30	0.25	presence of mucus	not calculated
156	COPD	40	0.33	presence of mucus	3.3
158	COPD	32	0.27	low recovery ratio (less than 30%)	3.5
163	COPD	20	0.17	presence of mucus	4.2
165	COPD	30	0.25	bloody sample/presence of mucus	54
166	COPD	25	0.21	low recovery ratio (less than 30%)	not calculated
168	COPD	10	0.08	low recovery ratio (less than 30%)	10.1
170	COPD	50	0.42	bloody sample	not calculated
174	COPD	25	0.21	low recovery ratio (less than 30%)	2.2
131	Fibrosis	20	0.17	diagnosis	not calculated
87	Idiopathic immunodeficiency	50	0.42	diagnosis	0.5
148	NSIP	40	0.33	diagnosis	not calculated
19	Pneumonia	30	0.25	diagnosis	12.3
118	Sarcoidosis	45	0.38	diagnosis	4.44
159	Sarcoidosis	40	0.33	diagnosis	not calculated

Table E4

RRID	Antigen	Fluorochrome	Clone	Volume (ul)	Laser	Detector	Catalog number	Company
AB_439781	CD3	PE/Cy7	UCHT1	3	488 nm	780/60	300420	Biologend
AB_396815	CD3	Alexa Fluor 647	UCHT1	5	633 nm	660/20	557706	BD Biosciences
AB_893322	CD4	PerCP/Cy5.5	RPA-T4	3	488 nm	695/40	300530	Biologend
AB_2564510	CD8	BV650	SK1	3	405 nm	655/15	344730	Biologend
AB_314174	CD11c	FITC	3.9	5	488 nm	530/30	301604	Biologend
AB_830693	CD14	APC/Cy7	HCD14	3	633 nm	780/60	325620	Biologend
AB_395798	CD14	FITC	M5E2	5	488 nm	530/30	555397	BD Biosciences
AB_2561354	CD16	BV605	3G8	2	405 nm	610/20	302039	Biologend
AB_314248	CD19	APC/Cy7	HIB19	5	633 nm	780/60	302218	Biologend
AB_314242	CD19	APC	HIB19	5	633 nm	660/20	302212	Biologend
AB_395992	CD33	FITC	HIM3-4	3	488 nm	530/30	555626	BD Biosciences
AB_2563466	CD45	BV711	HI30	3	405 nm	785/60	304050	Biologend
AB_396820	CD56	Alexa Fluor 647	B159	5	633 nm	660/20	557711	BD Biosciences
AB_2732786	CD56	BV510	NCAM16.2	5	405 nm	510/50	563041	BD Biosciences
AB_314496	CD66b	FITC	G10F5	3	488 nm	530/30	305104	Biologend
AB_2572566	CD66b	PE	G10F5	2	488 nm	585/42	12-0666-41	Thermo Fisher Scientific
AB_11154222	CD117	BV421	YB5.B8	5	405 nm	450/40	562434	BD Biosciences
AB_314580	CD123	FITC	6H6	5	488 nm	530/30	306006	Biologend
AB_2296056	CD127	PE	HIL-7R-M21	5	488 nm	585/42	557938	BD Biosciences
AB_2566234	CD203c	PE/Dazzle	NP4D6	5	488 nm	616/23	324623	Biologend
AB_11203707	CD294	APC	BM16	7	633 nm	660/20	350110	Biologend
AB_2571902	FcεRI	Alexa Fluor 700	AER-37	5	633 nm	730/45	334630	Biologend
AB_2629719	Siglec-8	PE/Cy7	7C9	6.5	488 nm	780/60	347111	Biologend
AB_893567	HLA-DR	PerCP/Cy5.5	L243	3	488 nm	695/40	307630	Biologend

Cell type	Expressed markers
AMs	CD45 ⁺ HLA-DR ⁺ CD66b ⁻ Autofluorescence ⁺
Neutrophils	CD45 ⁺ HLA-DR ⁻ CD66b ⁺ CD16 ⁺ Siglec-8 ⁻
Monocytes	CD45 ⁺ HLA-DR ⁺ CD66b ⁻ CD14 ⁺ Autofluorescence ^{lo}
DCs	CD45 ⁺ HLA-DR ⁺ CD66b ⁻ CD14 ⁻ Autofluorescence ^{lo} CD117 ⁻
Eosinophils	CD45 ⁺ HLA-DR ⁻ CD66b ⁺ CD16 ⁻ Siglec-8 ⁺
Mast cells	CD45 ⁺ HLA-DR ⁺ CD66b ⁻ CD14 ⁻ Autofluorescence ^{lo} FcεRI ⁺ CD117 ⁺ CD203c ⁺
CD4 ⁺ T cells	CD45 ⁺ CD3 ⁺ CD4 ⁺ CD8 ⁻
CD8 ⁺ T cells	CD45 ⁺ CD3 ⁺ CD4 ⁻ CD8 ⁺
Double positive T cells	CD45 ⁺ CD3 ⁺ CD4 ⁺ CD8 ⁺
Double negative T cells	CD45 ⁺ CD3 ⁺ CD4 ⁻ CD8 ⁻
B cells	CD45 ⁺ CD19 ⁺
NK cells	CD45 ⁺ CD3 ⁻ CD19 ⁻ CD56 ⁺
ILC1s	CD45 ⁺ CD56 ⁻ CD127 ⁺ CD117 ⁻ CRTH2 ⁻
ILC2s	CD45 ⁺ CD56 ⁻ CD127 ⁺ CD117 ⁻ CRTH2 ⁺
ILC3s	CD45 ⁺ CD56 ⁻ CD127 ⁺ CD117 ⁻ CRTH2 ⁻

Table E5

Table E7

sample	date_quartile	type	cells	diagnosis	stage	sex	age	BMI	fixed	smoking	ex_smoking	pack-years	asthma	medication	group	disease
INT:C079.mzML	3_17	AM	5*10~4	chronic cough		F	58	22.8	N	NA	NA	NA	NA	Y	ctrl	ctrl
INT:C080.mzML	3_17	AM	5*10~4	COPD	3/D	F	59	32	N	N	Y	50	N	Y	3_4	COPD
INT:C081.mzML	3_17	AM	4.7*10~4	COPD	2	M	70	20.2	N	N	Y	15	N	N	2	COPD
INT:C083.mzML	3_17	AM	5*10~4	COPD	2	M	64	36.3	N	N	Y	2925	N	Y	2	COPD
INT:C084.mzML	3_17	AM	5*10~4	COPD	4/D	M	61	18.9	N	N	Y	100	N	Y	3_4	COPD
INT:C103.mzML	4_17	AM	5*10~4	COPD	3	F	64	19.5	N	Y	N	62	N	Y	3_4	COPD
INT:C105.mzML	4_17	AM	5*10~4	COPD	3	M	60	29.3	N	N	Y	35	N	Y	3_4	COPD
INT:C123.mzML	1_18	AM	5*10~4	smoker		M	58	32.4	N	N	Y	40	NA	Y	ctrl	ctrl
INT:C135.mzML	1_18	AM	5*10~4	chronic cough		M	58	22.4	N	N	N	0	NA	N	ctrl	ctrl
INT:C137.mzML	1_18	AM	5*10~4	COPD	2	M	59	35.8	N	N	Y	10	N	Y	2	COPD
INT:C141.mzML	2_18	AM	5*10~4	chronic cough		M	60	29	N	N	N	0	NA	N	ctrl	ctrl
INT:C145.mzML	2_18	AM	5*10~4	COPD	2	F	46	37.5	N	Y	N	40	N	Y	2	COPD
INT:C149.mzML	2_18	AM	1*10~5	COPD	2	F	66	19.5	N	Y	N	40	N	Y	2	COPD
INT:C155.mzML	2_18	AM	5*10~4	COPD	2	M	54	26.2	N	Y	N	100	N	Y	2	COPD
INT:C176.mzML	3_18	AM	5*10~4	COPD	4	M	67	26.3	N	N	Y	60	N	Y	3_4	COPD