# Multi-omic profiling of pathogen-stimulated primary immune cells

## Authors

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## Summary

We performed long-read transcriptome and proteome profiling of pathogen-stimulated peripheral blood mononuclear cells (PBMCs) from healthy donors to discover new transcript and protein isoforms expressed during immune responses to diverse pathogens. Long-read transcriptome profiling reveals novel sequences and isoform switching induced upon pathogen stimulation, including transcripts that are difficult to detect using traditional short-read sequencing. Widespread loss of intron retention occurs as a common result of all pathogen stimulations. We highlight novel transcripts of *NFKB1 and CASP1* that may indicate novel immunological mechanisms. RNA expression differences did not result in differences in the amounts of secreted proteins. Clustering analysis of secreted proteins revealed a correlation between chemokine (receptor) expression on the RNA and protein levels in *C. albicans*- and Poly(I:C)-stimulated PBMCs. Isoform aware long-read sequencing of pathogen-stimulated immune cells highlights the potential of these methods to identify novel transcripts, revealing a more complex transcriptome landscape than previously appreciated.

## Introduction

Immune system responses within the context of an infection are shaped by the nature of the infection and by inter-individual variability, contributing to differential susceptibility to infections and to various diseases with an inflammatory component. Dynamic expression of transcripts and proteins in a range of cells responsible for the innate immune response is important to shape the first line of defense against a wide variety of pathogens[1]. Pattern recognition receptors (PRR) initiate acute inflammatory responses, activating signaling cascades that converge on various transcription factors. Multiple levels of regulation orchestrate the dynamic expression of transcripts and proteins, including transcriptional and post-transcriptional checkpoints such as mRNA splicing and protein translation. Examples of this include the regulatory role of alternative splicing of Toll-like receptors (TLR) and their downstream signaling factors[2,3].

Methods for investigating innate immune responses include *in vitro* stimulation of primary immune cells with pathogens or microbial components. These methods allow for specific investigation of host-pathogen interactions that shape the immune response elicited by specific cell types and have been under extensive investigation in research on the innate immune system[4,5]. Stimuli that are commonly used include molecules that stimulate a specific TLR, such as *E. coli* lipopolysaccharide (LPS) for TLR4[6], dsRNA mimicking Poly(I:C) for TLR3[7] and imidazoquinolines for TLR7/8[8]. Stimulation is also often elicited by live or heat-killed pathogens[9,10], which stimulate at the same time a broader range of PRRs[11,12].

Transcriptome characterization is traditionally performed using short read RNA sequencing. These sequencing approaches are limited by their short-read length (approximately 150-300 bp), necessitating the computational reconstruction of whole transcripts and making detection of different transcripts of the same gene inaccurate. This limitation is especially pronounced in immune biology, where tight regulation of isoform expression has previously been described to play a major role in processes, such as the expression of multiple IL-32 transcripts with different inflammatory potency[13] and alternative splicing of *CD45* in T cell activation[14]. Recent long-read sequencing approaches provide a more complete and accurate reflection of the transcriptome. Sequencing technologies provided by PacBio and

Oxford Nanopore allow for the sequencing of mRNA (or cDNA) molecules from the ultimate
3'-end to the ultimate 5'-end, which have given a more comprehensive view into the
complexity of the transcriptome. A number of studies have indicated that the isoform
landscape is much more complex than previously appreciated[15–17]. Long-read mRNA
sequencing has provided insight into regulatory mechanisms of immune responses, for
instance in alternative splicing in macrophages[18] , and allows for accurate sequencing of
complex transcripts in immune cells[19]. Further work on cell-type specific long-read
transcriptomes have shown preferential expression of transcripts in specific cell types[20].
88
The impact of the newly discovered transcripts as well as post-transcriptional processes can
only be fully understood by observing the proteome. Many studies have characterized the
transcriptomic landscape of the human immune response, but a multi-omics view of
immunity is necessary as mRNA profiles are not enough to understand immune
activation[21,22]. Transcript information can be leveraged to study the proteome, including
identification of novel proteoforms resulting from alternative splicing. Proteoforms
discovered by proteogenomics methodologies have already been found to have a role in
immunological processes, for instance in immune-regulating micropeptides[23] and tumor
neoantigen production[24].
98
99 Here, we stimulated peripheral blood mononuclear cells (PBMCs) with multiple microbial
100 stimuli *in vitro/ex vivo* and performed long- and short-read RNA sequencing and secretome
101 proteomics to gain insight into potential differences in immune response. We aim to
102 provide insight into the immune transcriptome and proteome of immune cells during innate
103 immune responses against a variety of pathogens.
104

## Material & methods
### Ex vivo PBMC experiments
Venous blood was drawn from five healthy donors[5] and collected in 10mL EDTA tubes.
Isolation of peripheral blood mononuclear cells (PBMCs) was conducted as described
elsewhere[25]. In brief, PBMCs were obtained from blood by differential density centrifugation
over Ficoll gradient (Cytiva, Ficoll-Paque Plus, Sigma-Aldrich) after 1:1 dilution in PBS. Cells
were washed twice in saline and re-suspended in serum-free cell culture medium (Roswell
Park Memorial Institute (RPMI) 1640, Gibco) supplemented with 50 mg/mL gentamicin, 2
mM L-glutamine and 1 mM pyruvate. Cells were counted using a particle counter
(Beckmann Coulter, Woerden, The Netherlands) after which the concentration was adjusted
to $5 \times 10^6$/mL. *Ex vivo* PBMC stimulations were performed with $5\times10^5$ cells/well in round-
bottom 96-well plates (Greiner Bio-One, Kremsmünster, Austria) for 24 hours at 37°C and
5% carbon dioxide. Cells were treated with lipopolysaccharide (*E. coli* LPS, 10 ng/mL),
*Staphylococcus aureus* (ATCC25923 heat-killed, $1\times10^6$/mL), TLR3 ligand Poly I:C (10 µg/mL),
*Candida albicans* yeast (UC820 heat-killed, $1\times10^6$/mL), or left untreated in regular RPMI
medium as normal control. After the incubation period of 24h and centrifugation,
supernatants were collected and stored at -80°C until further processing. For the RNA
isolation, cells were stored in 350 µL RNeasy Lysis Buffer (Qiagen, Rneasy Mini Kit, Cat nr.
74104) at −80°C until further processing.
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## RNA and protein isolation

RNA was isolated from the samples using the RNeasy RNA isolation kit (Qiagen) according to the protocol supplied by the manufacturer. The RNA integrity of the isolated RNA was examined using the TapeStation HS D1000 (Agilent), and was found to be ≥7.5 for all samples. Accurate determination of the RNA concentration was performed using the Qubit (ThermoFisher).

We extracted the secretome of the 24-hour stimulated PBMCs. To 250 μL of supernatant, 250 μL buffer containing 10% sodium dodecyl sulfate (SDS) and 100 mM triethylammonium bicarbonate (TEAB), pH 8.5 was added. Proteins were reduced by addition of 5 mM dithiothreitol and incubation for 30 minutes at 55˚C and then alkylated by addition of 10 mM iodoacetamide and incubation for 15 minutes at RT in the dark. Phosphoric acid was added to a final concentration of 1.2% and subsequently samples were diluted 7-fold with binding buffer containing 90% methanol in 100 mM TEAB, pH 7.55. The samples were loaded on a 96-well S-Trap$^{TM}$ plate (Protifi) in parts of 400 μL, placed on top of a deepwell plate, and centrifuged for 2 min at 1,500 x g at RT. After protein binding, the S-trap$^{TM}$ plate was washed three times by adding 200 μl binding buffer and centrifugation for 2 min at 1,500 x g at RT. A new deepwell receiver plate was placed below the 96-well S-Trap$^{TM}$ plate and 125 μL 50 mM TEAB containing 1 μg of trypsin was added for digestion overnight at 37°C. Using centrifugation for 2 min at 1,500 x g, peptides were eluted in three times, first with 80 μL 50 mM TEAB, then with 80 μL 0.2% formic acid (FA) in water and finally with 80 μL 0.2% FA in water/acetonitrile (can) (50/50, v/v). Eluted peptides were dried completely by vacuum centrifugation.

## Long-read library preparation and sequencing

Libraries were generated from one donor using the Iso-Seq-Express-Template-Preparation protocol according to the manufacturer's recommendations (PacBio, Menlo Parc, CA, USA). We followed the recommendation for 2-2.5kb libraries, using the 2.0 binding kit, on-plate loading concentrations of final IsoSeq libraries was 90pM (*C. albicans*, *S. aureus*, Poly(I:C), RPMI) and 100pM (LPS) respectively. We used a 30h movie time for sequencing.

The five samples were analyzed using the isoseq3 v3.4.0 pipeline. Each sample underwent the same analysis procedure. First CCS1 v6.3.0 was run with min accuracy set to 0.9. IsoSeq lima v2.5.0 was run in IsoSeq mode as recommended. IsoSeq refine was run with '--require-polya'. The output of IsoSeq refine was used as input for IsoQuant v3.1.2[26] with GRCh38.p13 v43 primary assembly from GENCODE. The settings were set for full length PacBio data, and quantification included ambiguous reads. In IsoQuant, transcripts were considered novel if their intron chains did not match intron chains found in GENCODE annotation version 39. Transcripts with fewer than 5 reads across all samples were excluded from further analyses (Supplemental table 1).

We sought to validate the novel transcripts identified using long-read sequencing using FANTOM5 CAGE data of CD14 monocytes (https://fantom.gsc.riken.jp/5/datafiles/latest/basic/human.primary_cell.CAGEScan/CD14% 2b%20monocyte%20derived%20endothelial%20progenitor%20cells%2c%20donor1.NCig100 41.11229-116C5.hg19.GCTATA.clusters.bed.gz) that allows for the identification of

171 transcripts with a matching TSS from this 5' sequencing data. Transcripts with novel 5' were
172 considered to be supported with a CAGE peak if within 150 basepairs from the TSS.
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<span style="color:#4472C4">Short-read library preparation and sequencing</span>
RNA input was normalized to 200 ng for all samples/donors and libraries were generated
using the QuantSeq 3' mRNA-Seq Library Prep Kit-FWD from Lexogen (Lexogen) in
accordance with the manufacturers' protocol. In order to ensure high quality libraries, two
separate preparations were performed, limiting the number of samples to 30 per
preparation. End-point PCR was performed with 19 – 22 cycles, as indicated by a
quantitative PCR on a 1:10 aliquot of a subset of double stranded cDNA libraries. Accurate
quantification and quality assessment of the generated libraries was performed using Qubit
dsDNA High Sensitivity assay (Thermo Fisher Scientific) and Agilent 2200 TapeStation (High
Sensitivity D1000 ScreenTape, Agilent). Molarity of individual libraries was calculated using
the cDNA concentration (Qubit) and average fragment size (TapeStation). Safeguarding
sufficient read-depth for each sample, libraries were split in two separate runs. In each run,
the baseline RPMI condition across all donors and time-points was included, in turn allowing
sequencing bias assessment. The cDNA libraries of 35 samples were pooled equimolarly to
100 fmol. After a final dilution of both pools to a concentration of 4 nM, they were
sequenced on a NextSeq 500 instrument (Illumina) with a final loading concentration of 1.4
pM.
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FastQC v0.11.5 (Babraham Bioinformatics) was used to assess the quality of the obtained
sequencing data, followed by removal of adapter sequences and poly(A) tails by Trim
Galore! V.0.4.4_dev (Babraham Bioinformatics) and Cutadapt v1.18[27]. Since QuantSeq reads
only provide coverage of the 3' end of transcripts, we generated a set of transcripts
representative of the full transcriptome by grouping transcripts based on unique 3'
sequences. Therefore, we separately mapped the filtered and trimmed reads to the long
read transcriptome with Salmon v1.9.0 in mapping-based mode with decoys[28].
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<span style="color:#4472C4">Differential expression analyses</span>
To measure differential gene expression from long-read RNA sequencing, low abundance
genes were filtered using a 10 CPM threshold with the conform package in python.
Differentially expressed genes (DEGs) and transcripts were calculated for each condition
versus control using the NOISeq R package[29] from the abundances generated with isoquant.
TMM normalization was chosen and q-value threshold for DE was set at 0.95.
206
DEGs were generated from the salmon-mapped short-read RNA sequencing data using the
samples from the same donor using NOISeq[29]. The two control samples (RPMI) per donor
were treated as technical replicates. TMM normalization was chosen and q-value threshold
for DE was set at 0.95. We validated the DEGs detected from long-read sequencing with
those generated with the short-read data by comparing the linear correlation of the
log2fold change values for each condition combination between both datasets using the
lm() R function.
214
215 The up- and downregulated DEGs per condition-control pair were analyzed for pathway
216 enrichment separately using gProfiler[29]. We used Gene Ontology biological process and

217  molecular function and TRANSFAC transcription factor motifs gene sets[30,31]. A term size filter
218  of between 100-500 was used to generate the final enrichment profiles.
219

Isoform switching
A first-pass isoform switching analysis was performed using swanvis v2.0[32]. For a second-
pass isoform switching analysis, the resulting gene-level isoform switch p-values were
imported into IsoformSwitchAnalyzeR v1.16.0 package in R[33]. Thresholds for isoform
switching were set at 10 DPI (differential percent isoform use) and nominal p-value <0.05.
Sequences corresponding to the significant isoform switches were analyzed with CPAT
v1.2.4[34], hmmscan v3.3.2 with Pfam[35], and SignalP5[36] as a part of the
IsoformSwitchAnalyzeR package.

Pathway analysis and gene network analysis of genes that were found to undergo isoform
switching was performed in Cytoscape[37]. Default pathway analysis was performed, filtering
for Gene Ontology Biological Process gene sets. An Enrichment Map was built from the
enriched gene sets with a Jaccard similarity cutoff of 0.4[38].

Genes found to undergo intron retention gains/losses and genes with domain gains/losses
were separately analyzed using gProfiler. We used Gene Ontology Biological Process gene
sets with a with a term size filter between 100-500 genes. We separately analyzed genes
with domain gains or losses were using dcGOR[39]. We used the gene ontology molecular
function gene sets with a term size filter between 100-500 genes.

LC-MS/MS analysis
Peptides were re-dissolved in 20 μL loading solvent A (0.1% trifluoroacetic acid in
water/acetonitrile) (98:2, v/v)) of which 4 μL was injected for LC-MS/MS analysis on an
Ultimate 3000 RSLCnano system in-line connected to a Q Exactive HF mass spectrometer
(Thermo). Trapping was performed at 10 μL/min for 4 min in loading solvent A on a 20 mm
trapping column (made in-house, 100 μm internal diameter (I.D.), 5 μm beads, C18 Reprosil-
HD, Dr. Maisch, Germany).   The peptides were separated on a 250 mm Waters nanoEase
M/Z HSS T3 Column, 100Å, 1.8 μm, 75 μm inner diameter (Waters Corporation) kept at a
constant temperature of 45°C. Peptides were eluted by a non-linear gradient starting at 1%
MS solvent B reaching 33% MS solvent B (0.1% formic acid (FA) in water/acetonitrile (2:8,
v/v)) in 100 min, 55% MS solvent B (0.1% FA in water/acetonitrile (2:8, v/v)) in 135 min, 97%
MS solvent B in 145 minutes followed by a 5-minute wash at 97% MS solvent B and re-
equilibration with MS solvent A (0.1% FA in water).

The mass spectrometer was operated in data-dependent acquisition mode, automatically
switching between MS and MS/MS acquisition for the 16 most abundant ion peaks per MS
spectrum. Full-scan MS spectra (375-1500 m/z) were acquired at a resolution of 60,000 in
the Orbitrap analyzer after accumulation to a target value of 3,000,000. The 16 most intense
ions above a threshold value of 15,000 were isolated with a width of 1.5 m/z for
fragmentation at a normalized collision energy of 28% after filling the trap at a target value
of 100,000 for maximum 80 ms. MS/MS spectra (200-2000 m/z) were acquired at a
resolution of 15,000 in the Orbitrap analyzer.
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### Protein identification and quantification

Two search databases were constructed; one database for proteoform detection and one database for quantification. The database used for sensitive detection of proteoforms was generated using a slightly adapted version of the Long Read Proteogenomics pipeline by Miller *et al*[40]. Since the pipeline uses a different long-read transcriptomics tool, small syntax adjustments were made to accommodate the use of Isoquant output. Additionally, a custom script was written to have Isoquant output mimic the required input format. The pipeline generated a GENCODE-PacBio hybrid database. The proteome from *C. albicans* (taxon ID 5476) and *S. aureus* (taxon ID 1280) were downloaded from UniProt and added to the search database. The search database used for quantification was created by downloading the proteome from *H. sapiens* (taxon ID 9609), *C. albicans* (taxon ID 5476) and *S. aureus* (taxon ID 1280) from UniProt. Metamorpheus default contaminants were added to both search databases.

Mass spectra were identified using Metamorpheus v1.0.0[41]. The Human Proteome Project Mass Spectrometry Data Interpretation Guidelines version 3.0 were applied[42]. Quantification was performed using FlashLFQ v 1.2.4.294[43] with all five individuals set as biological replicates and the two control (RPMI) samples per individual set as technical replicates. The following options enabled: normalization, shared peptide quantification, Bayesian fold change analysis, and match between runs (Supplemental table 2). An adapted version of SQANTI protein was used to search for novel peptides in the Metamorpheus identifications. Enrichment of secreted proteins was determined using the predicted secreted proteins from Human protein atlas[44] as reference.

### Protein clustering

FlashLFQ raw protein expression values originating from the quantification database search were first square root transformed. To normalize for donor effects, the mean protein expression value per gene/individual was subtracted from all the expression values from the same gene/individual. Then z-score normalization was performed across all individuals per gene. K-means clustering was then performed using the kmeans() function in R with seed #82 and default parameters. We found four clusters to optimally represent the data according to the elbow plots (Supplemental figure 1). A heatmap was constructed with those clusters using the ComplexHeatmap package[45]. The proteins identifiers assigned to cluster #4 were converted to gene names and analyzed using gProfiler for enrichment analysis using both Gene Ontology Biological Process and Molecular Function gene sets. We further analyzed the protein found to form cluster 4 through a protein network analysis in Cytoscape[37].

### Results

We stimulated PBMCs from five donors with four different microbial stimuli, mimicking bacterial (*E. coli* LPS, *S. aureus*), viral (Poly(I:C)) and fungal (*C. albicans*) infections. PBMCs were stimulated for 24 hours. RPMI incubation was used as a negative control (Figure 1A). To characterize full-length transcript structures, we performed long-read sequencing on PBMCs from one donor (Figure 1B). Additionally, shotgun proteomics data was generated from supernatants of the samples from all five donors. The proteomics data serves to corroborate differential gene/transcript expression and provide evidence of the protein-

coding potential of novel transcripts identified through long-read RNA sequencing (Figure
1C). Short-read 3' sequencing data of all five donors was generated to validate differential
gene expression data generated from long-read RNA sequencing (Figure 1D).

Long read transcriptomes of both control and pathogen-stimulated conditions show novelty
Sequences detected using long-read sequencing were categorized in terms of novelty
according to their intron chains. Transcripts are divided into three categories that
encompass reference transcripts (GENCODE), novel in catalog (transcripts that contain
annotated introns) and transcripts that are novel not in catalog (containing unannotated
introns) (Figure 2A). We identified a total of 37,312 unique transcript sequences from
11,872 genes across all samples. The majority of transcripts were in protein coding genes
(Supplemental figure 2A) including ~10% immune-related genes (Supplemental figure 2B).
We found 47.4% of detected transcripts to be novel, while these accounted for only 20.3%
of the total reads (Figure 2B). The distribution of reads per novel transcript was similar to
that of known transcripts with a slight skew towards lower abundance (Supplemental figure
3A). Exon elongations were the most observed feature distinguishing novel from known
transcripts, occurring in nearly a third of the novel transcripts found in RPMI. This was
similar for the stimulated conditions (Figure 2C, Supplemental figure 3B). The percentage of
novel transcripts and transcript deviations were similar for all conditions (Figure 2D). To
corroborate the existence of novel transcripts, we analyzed FANTOM5 CAGE peaks in the
vicinity of the transcription start sites for novel transcripts with novel 5' ends. We found
8,233 (51.3%) novel 5' end transcripts across all conditions to be supported by a CAGE peaks
from unstimulated human monocytes (within 150 nucleotides)[46].

Principal component analysis of the expression levels for each transcript indicated that
stimulated conditions were more similar to each other than to RPMI. *S. aureus* and *C.*
*albicans* were most similar to each other (Figure 2F). Genes and transcripts expressed were
similar in the stimulated conditions with average Jaccard similarity indices of 0.9 and 0.82
for genes and transcripts, respectively (Figure 2G). Novel transcripts had similar Jaccard
indices to each other than for known transcripts (not shown). Differential expression
analysis yielded an average of 949 DEGs and 2,076 differentially expressed transcripts per
condition (Supplemental figure 4, Supplemental table 3-4).

We validated the DEGs through 3' transcript counting (QuantSeq)[47]. We gathered a set of
representative transcripts based on sequence differences at the 3' end of transcripts
(29,760 transcripts, 79.8% of total) and investigated the correlation of differential
expression in the long-read sequencing data with the separately generated short read
dataset of the same donor. The DEGs that overlapped between both datasets correlate well
($R^2$ 0.62-0.81). Best matching pairs of stimulated conditions between the short- and long-
read confirmed the concordance of both sequencing approaches (Supplemental figure 5,
Supplemental table 5).

Pathogen stimuli display upregulation of different pathways
Differential gene expression analysis using the long-read sequencing data resulted in a total
of 1,733 genes that were differentially expressed in stimulated conditions compared to
control. We performed pathway analysis for each condition using gProfiler[48] (Supplemental
table 6). By overlapping the gene sets enriched in each of the four conditions, we discerned

biological processes/functions specific to certain pathogen-stimulated conditions. There are a lot of constants in host response regardless of the pathogen, and indeed the largest set of pathways was in the overlap between all stimulated conditions (211 pathways, Figure 3A). This set has an enrichment of genes involved in type II interferon (IFN-γ) responses. Genes involved in tertiary and specific granules, which play a role in the defense against pathogens were found to be enriched among upregulated genes in all conditions. Surprisingly, we also find these and related gene sets to be enriched among downregulated genes as a result of *S. aureus* and Poly(I:C) stimulation, potentially a result of the regulation of the inflammatory response. Further gene sets included the response to molecules of bacterial origin (including LPS), innate immune response signaling such as PRR signaling, antigen processing and presentation and IL-1 production (Figure 3B).

Some pathogen-stimulated conditions had more enriched pathways in common than others. There was a notable overlap of 131 gene sets enriched in *C. albicans-, S. aureus-* and Poly(I:C)-stimulated conditions. Some of these were common to the set overlapping between all conditions, such as interferon responses. The LPS-excluding set showed particular enrichment related to viral processes such as the defense against viruses, regulation of the viral lifecycle, likely due to interferon-stimulated gene expression, such as *STAT1, OAS1/3, OASL and IFIH1*. Also, transcription factor binding matches (TRANSFAC) such as *IRF-2, 5, 8* and *9* were enriched, reflecting downstream signaling through various signaling pathways leading to the regulation of the production of interferons and immune cell development (Figure 3C)[49].

LPS and Poly(I:C) were the 2 stimuli with the most enriched pathways unique to a single stimulus. For 55 gene sets unique to LPS, there was a downregulation of T cell receptor signaling, in part due to the downregulation of *CD4* expression, which has previously been described as a result of endogenous production of TNF-α and IL-1β as a result of LPS stimulation[50]. We further found an upregulation of gene sets involved in metabolic processes such as oxidoreductase complexes and cellular responses to oxygen, possibly reflecting metabolic changes previously described to occur in immune cells such as monocytes upon LPS stimulation[51]. Furthermore, there was an upregulation of genes involved in humoral immune responses (Figure 3D). For 53 gene sets enriched uniquely in Poly(I:C), we found functions including viral gene expression, apoptosis related signaling (regulation of cysteine-type endopeptidase activity) and B-cell related gene sets such as increased antibody levels and BCR signaling. Finally, there was an enrichment of MHC class II antigen presentation (Figure 3E).

### Isoform switches highlight transcriptome differences between conditions and control

Isoform switching (IS) genes are defined by a change (increase/decrease) of expression of a particular transcript isoform as measured by percent of total reads for a gene. In different samples/conditions, a particular transcript isoform may comprise a different isoform fraction (dIF) value for a given gene. Here, a change of at least 10% (0.10 dIF) in control and the opposite change (decrease/increase) of expression of a different transcript isoform in the same gene of at least 10% in the pathogen-stimulated condition is considered an IS.

A total of 999 IS were detected in 398 genes. Nearly half (N=192, 48.2%) of these IS genes were unique to their respective stimulus conditions, while 10.3% were found in all

conditions (N=41) (Figure 4A, Supplemental table 7-8). The majority of genes demonstrating
IS were not differentially expressed in their respective conditions (327 genes; 77%). Most
genes that were found to undergo IS displayed only one IS instance (Supplemental figure
6A). Pathway analysis of genes undergoing IS were enriched for gene sets involved in
metabolic processes, mRNA splicing, protein transport and catabolism. Furthermore,
immune and stress-related pathways such as MHC type I antigen processing and transport
through vesicles, inflammasomes, oxidative stress and apoptosis were found to be
represented in genes undergoing IS (Figure 4B, Supplemental tables 9-13).
411
We sought to understand the molecular consequences of IS upon pathogen stimulation by
categorizing the differing features of the isoform pairs involved in the switch. Each of the IS
was annotated with one or more of the following predicted protein characteristics: change
in ORF length, ORF gain/loss, domain gain/loss, NMD sensitivity, intron retention (IR)
gain/loss, coding probability (ORF presence), and signal peptide gain/loss. These
consequences are not independent and often multiple consequences could be attributed to
one IS (Supplemental Figure 6B). We observed general IS trends on a genome-wide scale
(Supplemental figure 6C, Supplemental table 14). Strikingly, we found IR loss to be the most
common consequence of IS in this dataset. Isoforms with retained introns comprised a
higher isoform fraction for genes in the control condition, while their respective intron-
excluding counterparts had a higher isoform fraction for genes in the pathogen-stimulated
conditions. Genes displaying loss of IR were enriched for pathways involved in mRNA
processing, including spliceosome-related gene sets, antigen processing and IL-1 production
(Supplemental figure 7). IR has previously been described as a regulatory mechanism of RNA
processing, splicing, vesicle transport and type I interferon production in the development
of various immune cell types, including macrophages[52,53], granulocytes[54] and B cells[55,56]. Our
findings support previously described associations of IR losses in immune-related processes,
and adds new genes regulated by IR loss during immune responses (Supplemental figure 7,
Supplemental table 15).
431
432  In addition, we found a higher proportion of transcripts to have domain gains than domain
433  losses. This could indicate that stimulation by a pathogen causes a gene to switch expression
434  to a transcript isoform that codes for a protein with an extra function. Other observed
435  trends included longer ORFs and NMD insensitivity in transcript isoforms induced by
436  pathogen stimulation (Figure 4C).
437
Since the addition or loss of domains could directly reveal protein function changes, we
explored the IS that had this consequence type. We found that genes with domain gain/loss
(N=158, Supplemental table 16) were enriched for involvement in various catabolic
processes. We also found enrichment of T cell activation genes, an effect previously
described as a functional consequence of CD8+ T cell co-stimulation[57]. Other enriched gene
sets include leukocyte cell-cell adhesion and activation and general innate immune response
genes (Supplemental table 17). When looking more specifically at the molecular functions of
the gained domains themselves, we found an enrichment of domains with potassium
channel regulator activity, kinase- and transferase activity concerning phosphorus-
containing groups and nucleic acid binding. These results potentially indicate functional and
cell-type specific effects of domain gains as a result of IS in immune responses
(Supplemental figure 8, Supplemental table 18).

Novel transcripts play an important role in IS. Of the 999 IS, more than half (N=592) had at
least one novel transcript involved in the IS. In most cases (N=438), the switch was from a
novel transcript to a known transcript (Figure 4D, Supplemental table 19). Compared to IS
cases where only known transcripts were involved, the IS consequences were more often
NMD insensitivity and IR loss (Figure 4E). Conversely, shorter ORFs, domain losses and NMD
sensitivity were more common effects when the IS was from a known to a novel transcript
isoform. In conclusion, the unstimulated condition is characterized by the presence of many
novel transcripts with retained introns, which are difficult to detect with short read
sequencing. IR is likely a mechanism to prepare a cell for fast action after an immune
stimulus, when splicing of the retained intron could quickly generate a functional transcript
with coding potential, which has been for instance been described in CD4+ T cells[58].
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A novel read-through transcript including *CARD16* and *CASP1*
As an example of a remarkable finding with possible biological impact once validated, we
identified a read-through transcript that includes both *CARD16* and *CASP1* (Figure 5A). Read-
through transcripts involve transcription that extends beyond the normal polyadenylation
site (PAS), terminating at the PAS of an adjacent gene or other nearby locus[59]. These
transcripts have been found to be expressed in specific circumstances, including malignancy
and infection[59,60]. This particular novel transcript encompasses the coding region of *CASP1*
and has an extended 5' UTR which spans *CARD16,* and thus contains two ORFs. This IS was
annotated as an intron retention loss, as the novel transcript loses an intronic region in its 3'
UTR (Figure 5B). Both the known and novel transcripts in this IS are predicted to be coding
(both 100%). *CASP1* was found to be differentially expressed upon Poly(I:C) stimulation
(log2FC 1.73, p=0.049; Figure 5C). The isoform expression of the known transcript was found
to decrease upon Poly(I:C) stimulation, while the novel transcript was found to increase
(Figure 5D). This is further reflected in the isoform fraction, increasing from 8.3% to 24.8%,
while the known transcript decreased from 85.5% to 74.2% (Figure 5E).
478

*CARD16* and *CASP1* both have a function in proinflammatory IL-1β signaling, where *CARD16*
has been shown to play a role in *CASP1* assembly, although there remains discussion on the
exact regulatory effect of *CARD16* on this process [61,62]. We have identified an IS specifically
for Poly(I:C) stimulation, where a novel transcript of *CASP1* was found to harbor *CARD16* in
its 5' UTR was upregulated upon stimulation. This finding could suggest a novel molecular
mechanism in IL-1β signaling, potentially through the regulation of *CASP1* by its regulator
*CARD16*.
486

A novel coding transcript of *NFKB1*
We identified a novel *NFKB1* transcript that demonstrated IS in all four conditions. This
novel transcript was shorter than the canonical transcripts (Figure 6A). Further analysis
revealed that the novel transcript start site was supported by multiple nearby CAGE peaks
(Figure 6B). Strikingly, this novel transcript lacks a part of its Rel homology domain, a
conserved domain responsible for functions such as dimerization and DNA binding (Figure
6C)[63]. *NFKB1* was not found to be significantly differentially expressed, although gene
expression was found to be higher in pathogen-stimulated condition compared to
unstimulated condition (only *C. albicans* shown, Figure 6D). The expression of the novel
transcript was found to increase upon pathogen stimulation (Figure 6E). This is reflected in

the isoform fraction, which increases from 23.5% to 50.7%, while the known transcript decreases from 39.0% to 21.2% (Figure 5F).

*NFKB1* plays a central role in immune responses, regulating the response to infections through transcriptional activation[57]. Furthermore, the Rel homology domain region is known to harbor disease-causing variants responsible for common viable immunodeficiency (CVID)[64], highlighting the importance of this domain in normal B cell function. This finding could suggest a novel regulatory mechanism of *NFKB1*.

## Isoform switching in *CLEC7A* and *OAS1* in a stimulus-specific manner

We sought to identify genes with stimulus-specific IS patterns. We identified an IS in *CLEC7A,* which codes for Dectin-1, a receptor that recognizes fungal glucans, triggering the immune response[65]. While this gene was not differentially expressed upon pathogen stimulation, we did identify an IS specific to *C. albicans* stimulation in this gene, involving a decrease in expression of an NMD sensitive transcript, with the increase in expression of the canonical coding transcript and a non-coding transcript (Supplemental figure 9A). In contrast, IR loss in *CLEC7A* was previously identified as a result of stimulation with multiple pathogen stimuli in monocytes. Additionally, no difference in gene expression levels was found between IAV-stimulated and resting cells, where the change in splicing was most pronounced[66]. While we find IR loss in *CLEC7A* specifically upon *C. albicans* stimulation, this could therefore also indicate a shared transcriptional response to pathogen stimuli.

Additionally, we identified an IS involving *OAS1*, which is involved in antiviral immunity. This gene is differentially expressed in response to *C. albicans, S. aureus* and Poly(I:C) (Supplemental figure 9B). We identified an IS in this gene resulting in an intron loss and a domain gain. This IS was only observed for Poly(I:C) stimulation, potentially indicating this transcript is necessary for antiviral immune responses (Supplemental figure 9C). Previous work has identified common *OAS1* haplotypes responsible for a decrease in protein abundance through the expression of NMD sensitive transcript p42, which contributes to COVID-19 severity[67]. We find this transcript to be downregulated upon Poly(I:C) stimulation. However, the transcript we find to be upregulated lacks the prenylation site needed for antiviral function, as shown for p46[68].

## Detecting secreted peptides

We sought to obtain evidence of the protein-coding potential of novel transcripts found through long-read RNA sequencing. Mass spectrometry was performed for 30 secretome samples from five donors' stimulated PBMCs, which includes the samples from the individual for which long read RNA sequencing was performed (see methods). These include 2 control samples and 1 of each 24-hour pathogen stimulation condition for each individual.

We designed a search database comprising all proteins that we suspected could be in the sample. This includes the GENCODE human proteome, the proteomes of the pathogens used, as well as ORFs derived from novel transcripts found using long-read RNA sequencing. Novel transcripts do not always correspond to novel ORFs; 32% of the novel transcripts had an ORF that was present in the GENCODE reference database (Supplemental Figure 10). In the collection of 30 samples, a total of 38,703 peptides from 15,964 proteins were identified. We found 404 (7.37%) of identified proteins were known to be secreted

according to the human protein atlas, which constitutes a significant enrichment (OR=2.12, p=3.88x10$^{-21}$, Fisher's exact test). We did not detect microbial proteins in the samples. Many of the novel ORFs predicted from the transcriptome have high similarity to GENCODE ORFs, resulting in a small number of novel peptides that could uniquely identify these. After rigorous filtering, we were unable to confidently identify peptides that mapped uniquely to the predicted novel ORFs.

## Wider deviations in expression in the secretome

To assess whether differences in transcript expression resulted in differences in the amounts of secreted proteins, we performed a label-free quantification of the proteins in the cells' supernatants. Using PCA, we found that a large portion of variation in the proteome was explained by inter-individual differences and that these differences were larger than the differences induced by the immune stimuli (Supplemental figure 11).

We found a total of 418 differentially expressed proteins (DEPs) between the stimuli and control when controlling for individual variation. Differential protein expression was not equally distributed between stimuli with over a third (N=131) of the DEGs unique to Poly(I:C) stimulation (Supplemental figure 12A). With the exception of the *S. aureus* condition, more proteins were significantly downregulated than significantly upregulated in the secretome (Supplemental figure 12, Supplemental table 20). We found few overlapping proteins per condition, which could indicate either a high specificity in response to different pathogens or a lack of protein secretion in a subset of samples.

To determine which explanation is more likely, we visualized the specific (groups of) proteins associated with response stemming from the stimuli. We clustered protein expression values normalized by individual and stimulus (Figure 7A, Supplemental table 21). The clustering revealed a separation between poly(I:C) samples and the rest of the stimuli. *C. albicans* showed a large overlap with poly(I:C) in the protein expression profiles. Some *C. albicans* samples were grouped with poly(I:C) samples, which confirms the results from the differential protein expression analysis (34 common DEPs, Supplemental figure 12A). Other stimulus conditions could not reliably be separated from RPMI.

We identified a cluster of proteins that are highly expressed in Poly(I:C) and *C. albicans* (cluster 4, Figure 7A). This group of proteins is enriched for genes with functions in leukocyte migration and chemotaxis, exemplified by neutrophil migration. We identified further enrichments of gene sets involved in the response to IL-1, humoral antimicrobial response, and cellular responses to LPS and type II interferons. Analysis of the molecular functions of these genes indicated an enrichment of cytokine activity and receptor binding, GPCR receptor binding and various catalytic functions, likely due to immune cell differentiation and immune responses involving the degradation of extracellular matrix proteins during immune cell migration[69] (Figure 7B, Supplemental table 22). We further assessed the proteins in cluster 4 through a gene network analysis (Figure 7C, Supplemental table 23-24). Of the 84 proteins in this network, 61 were differentially expressed on the protein level (72.6%, any condition). Of these DEPs, 18 are involved in cytokine signaling (29.5%), of which 13 genes are chemokines (71.2%). A high proportion of proteins are found in the extracellular region (n=47, 77.0%), for instance through secretion in granules. The biological functions of the DEPs in cluster 4 reflect those found for the complete set of

591    proteins in cluster 4, mainly corresponding to pathways associated with functions in
592    neutrophil migration and chemotaxis (Supplemental table 25). As these pathways are not
593    necessarily specific to these two stimuli, this may indicate Poly(I:C) and *C. albicans* may be
594    more effective at eliciting differential protein secretion or have less delay in secretion
595    compared to the other stimuli.
596
Comparison with RNA expression
As established earlier, a multi-omics approach is currently the best way to understand the
human immune response. Correlation between the RNA and protein levels, or lack thereof,
can provide important clues about the host response to pathogens. To assess the
correlation of differential gene and protein expression levels, we assessed the concordance
of differential expression on the RNA and protein level. This metric corresponds to the
percentage of genes for which differential expression on both levels matched in
directionality (out of all genes where DE was observed on both levels) (Figure 7D,
Supplemental table 26).
606
We observed an overall poor concordance of directionality and fold change of expression
levels at the RNA and protein levels in the different stimulus conditions, with the exception
of *C. albicans* with 73% overall concordance. We overlaid the genes in group 4 from our
clustering analysis with the genes found to be DE on both RNA and protein levels. There was
an overrepresentation of the genes in this cluster in the total group of dual-level DE genes
(OR=6.99, p=4.813e-16). Further analysis of concordant differential expression matches
arising from proteins in cluster 4 (triangles in Figure 7D), we observed high concordance in
the genes induced by *C. albicans* and/or Poly(I:C). Directionality concordance for Poly(I:C)
and *C. albicans* for genes in in cluster 4 was significantly higher than overall directionality
concordance (p=0.0313 Poly(I:C), p=0.0003 *C. albicans*, Fisher's test one-tailed). The cluster
4 proteins in the LPS and *S. aureus* conditions are in the lower right quadrant, indicating that
the increase of RNA translated into a decrease of secreted proteins for these genes (Figure
7D).
620
We hypothesized in the IS analysis that a major regulatory mechanism in the host response
to pathogens was the loss of intron retention for rapid protein generation. We cross-
referenced the secreted proteins to support this conjecture. By overlapping upregulated
isoforms from intron retention loss events, we found 20 cases from 7 genes (Supplemental
table 27). Of these genes, 2 were upregulated on the protein level, supporting our
hypothesis. The genes were *GZMB* and *B2M*, which are important immune-regulatory genes
that are both secreted[70,71]. Considering the remaining 5 genes that were *downregulated* on
the protein level, however, this is not convincing evidence that intron retention loss in
general provides a rapid increase of protein production.
630
Discussion
The identification of novel transcripts and subsequent production of additional protein
isoforms could help identify molecular mechanisms that play a role in various biological
processes, including immune responses. Various immune system processes have previously
been found to be regulated by alternative splicing [72,73 74 75]. Immune responses display
significant inter-individual differences. Donor-specific effects such as sex and ancestry have
been shown to significantly influence the transcriptome. Previous studies have further

shown the impact of QTLs in the heritability of cytokine production capacity[5,76–78]. However,
the effect of these processes on host defense mechanisms against pathogens, together with
the large inter-individual differences in transcription and protein expression, remain to be
elucidated.
642
We have generated a long-read transcriptome of pathogen-challenged primary immune
cells (PBMCs) together with the secreted proteome to investigate mechanisms underlying
immune responses during infection. We described the accurate identification of known and
novel transcripts in both control and pathogen-challenged conditions. Of these transcripts,
we identified a subset that is differentially expressed as a result of pathogen stimulation,
which we validated by short read RNA sequencing data (including 4 additional individuals)
and publicly available CAGE data from neutrophils.
650
We examined isoform switching that occurred as a result of pathogen stimulation, insight
into transcripts that may play a role in pathogen responses. On a genome-wide level,
widespread intron retention losses were observed. Retained introns that rendered the
transcript unusable in the control condition were spliced out as a result of microbial
stimulation; a trend we observed in all conditions regardless of microbe. We postulate that
these are examples of unproductive splicing in unstimulated cells switching to productive
splicing after stimulation enabling fast production of proteins relevant for the immune
response. Genes that undergo intron retention loss mainly have functions in mRNA splicing
and processing and in immunity. Tissue- or cell-type specific unproductive splicing has been
widely observed as an autoregulatory process for mRNA splicing factors[79], which is
supported by our data in immune cells. We were however not able to confirm changes in
protein expression of genes that underwent IR losses using our secretome proteomics data,
likely because these proteins are not generally secreted. A couple of pertinent examples
have been illustrated in greater detail. We identified an IS specific to the viral stimulus that
involves a novel read-through transcript of CASP1 and CARD16. We found an instance of IS
to a novel NFKB1 transcript with a shortened DNA binding domain that was found in all four
conditions. Additionally, we describe IS in CLEC7A and OAS1 for C. albicans and Poly(I:C),
which highlight stimulus-specific alternative splicing. Taken together, these results highlight
the potential for long-read sequencing to accurately resolve novel transcripts with potential
relevance in immune responses, including intron retention loss events that are generally
difficult to detect using short-read sequencing.
672
The extent to which conclusions can be drawn about immune response mechanisms is
limited by the low sample size for long-read sequencing. In this explorative study meant to
provide insights into the novel technical possibilities utilizing latest sequencing approaches,
we generated long-read sequencing data for only a single individual because of the
expensive nature of this technology in combination with the required sequencing depth and
the number of conditions studied. This design did not allow us to investigate the inter-
individual differences in the transcriptome. Novel transcripts that were detected could thus
be specific to this individual. Future follow-up including the sequencing of more individuals
using accurate long-read sequencing methods and functional studies could provide
additional insight into the more general relevance of these transcripts in immune responses.
This study focused on the appraisal of the transcriptome and proteome in PBMCs, which
consist of multiple cell types. Use of freshly isolated PBMCs accurately represents the

complete immune cell population in the peripheral blood and allows for communication between cell types during pathogen stimulation, thereby potentially giving an accurate representation of this cell population *in vivo*. However, no information on cell type specificity of transcripts is available. This could be resolved by recent developments in single cell long-read sequencing[80].

The proteome, in contrast, was generated for all samples from all 5 individuals and highlighted significant differences between the secretome of individual donors, before and after response to immune stimuli. Concordance between the transcriptome and proteome levels was high in Poly(I:C) and *C. albicans*, and lower in LPS and *S. aureus*. We found that genes with high correlation on the RNA- and protein levels form a cluster of protein expression, separating the former two stimuli from the latter. These proteins are enriched for secreted immune-related proteins, indicating that pathogen stimulation successfully led to secretion of relevant proteins. This would indicate that cells have responded faster to the Poly(I:C) and *C. albicans* stimuli than to the LPS and *S. aureus* stimuli, because RNA and protein were isolated simultaneously from our samples. Delay in protein production after expression of an mRNA may partially explain the lack of correlation of differential expression on RNA and protein level. This delay is presumably even longer in the secretome as proteins need to be first produced and subsequently secreted[81].

We focused our study on the secretome to reduce the complexity of the protein mixture analyzed, and to obtain better peptide coverage of the secreted proteins that play an important role in immune signaling. However, this limited our view on the complete proteome affected by immune stimuli. Also, there is the added complication that only a small number of peptides exist that could discriminate between proteoforms. To detect the proteoforms derived from our long-read sequencing data, much deeper shotgun proteomics must be performed[82]. These limitations are reasons why no evidence of novel transcripts could be validated with the proteome.

Multi-omics approaches are a promising method to further our understanding of immune responses. Our study scratches the surface of biological insight to be reaped from a combination of multi-omics and long-read sequencing data and was hindered only by the aforementioned limitations in the samples themselves. Removing these limitations will undoubtedly result in deeper mechanistic understanding and will translate into better outcomes for patients. Insights gained from this methodology can be used immediately in rare disease diagnostics applications, such as the reannotation of variants using more accurate reference transcriptomes for specific tissues[83], contributing to the development of more personalized medicine.

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## Author contributions
Conceptualization: RS, PJV, AH, PACH; data curation: RS; formal analysis: RS; investigation: RS, EEV, CIM, TVR, TH; resources: SK, MS; software: RS, TVR; supervision: MM, MGN, PJV, AH, PACH; visualization: RS, EEV; writing—original draft: RS, EEV; writing—review and editing: All authors. All authors read and approved the final manuscript.

## Keywords
Long-read RNA sequencing, transcriptomics, proteomics, innate immune response, alternative splicing, isoform switching, protein secretion

## Declaration of interests
### Competing interests
The authors declare no competing interests.

## Consent for publication
Not applicable

## Ethics approval and consent to participate
PBMCs were retrieved form healthy, anonymized donors, as part of the human functional genomics project (HFGP). The HFGP study was approved by the Ethical Committee of Radboud University Nijmegen, the Netherlands (no. 42561.091.12). Experiments were conducted according to the principles expressed in the Declaration of Helsinki. Samples of venous blood were drawn after informed consent was obtained.

## Availability of data and material
Raw PacBio sequencing data and transcriptome is available on EGA under accession number EGAS00001006779. Raw QuantSeq sequencing data is available on EGA under accession number EGAS50000000007. The mass spectrometry proteomics data have been deposited to the ProteomeXchange Consortium via the PRIDE[84] partner repository with the dataset identifier PXD045237 and 10.6019/PXD045237. Scripts used to generate the results described in this paper can be found at https://github.com/cmbi/hpi_isoseq_paper.

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Figure legends
Figure 1: Experimental setup. A) Human peripheral blood mononuclear cells (PBMCs)
isolated from five donors were exposed to four different pathogenic stimuli and analyzed
after 24 hours. B) PacBio long read RNA-sequencing was performed on samples from one of
the five donors. Long-reads were used to estimate differential transcript expression and
isoform switching. C) The supernatant from all samples (all donors) was collected and
peptides were detected to quantify protein levels in the secretome. D) Short read RNA
sequencing (QuantSeq) was performed on all samples (all donors) and differential
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996

Figure 2: Transcriptome novelty in the control condition and comparison between stimuli
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novel combination of annotated introns. Novel not in catalog (green) contains one or more
unannotated introns. B) Reads (top) and unique transcripts (bottom) of events in each pre-
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1009 Figure 3: Differential pathway analysis originating from differentially expressed genes on the
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1014
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1026
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1054  Supplemental figures

1055  Supplemental figure 1: *Elbow plots using kmeans clustering*. Elbow plots to determine the
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1058  Supplementary figure 2: *Gene types where novel transcripts are found*. A) Most common
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1075

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1078  from 145 genes.

1079

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1092

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1094  *secretome of all samples.* A) Colored by individuals 1-5. B) Colored by stimulus condition.

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1118    *switching.* Generated using Cytoscape.

1119

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1121    *switching.* Generated using Cytoscape.

1122

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1124    using Cytoscape.

1125

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1147 Supplemental table 21: *Proteome heatmap expression values.*

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1149 Supplemental table 22: *Pathway analysis of proteins in cluster 4.*

1150

1151 Supplemental table 23: *Nodes from the network analysis of proteins found in cluster 4.*
1152 Generated using Cytoscape.

1153

1154 Supplemental table 24: *Edges from the network analysis of proteins found in cluster 4.*
1155 Generated using Cytoscape.

1156

1157 Supplemental table 25: *Pathway analysis of differentially expressed proteins found in cluster*
1158 *4.*

1159

1160 Supplemental table 26: *Correlation between differentially expressed genes and proteins.*

1161

1162 Supplemental table 27: *Proteome evidence for intron retentions.*

**A.**

LPS  *S. aureus*  Poly(I:C)  *C. albicans*

N=5

24hr stimulation

Peripheral blood mononuclear cells

**Transcript discovery**

**B.**

N=1

PacBio long read sequencing (IsoSeq)

Transcript detection

Differential gene/transcript expression
Isoform switching

**Secretome proteomics**

**C.**

N=5

LC-MS/MS Proteomics

Peptide identification

Differential proteoform expression

**Validation**

**D.**

N=5

3' mRNA sequencing (QuantSeq )

Differential gene expression validation

**A.**

**B.**

GO Biological Process

- Neutrophil migration
- Response to IL-1
- Leukocyte chemotaxis
- Antimicrobial humoral response
- Cellular response to LPS
- Cellular response to type II IFN

GO Molecular Function

- Cytokine activity
- GPCR binding
- Cysteine-type endopeptidase activity
- Glycosaminoglycan binding
- Serine hydrolase activity

Enrichment

**D.**

RNA log2 Fold-Change / Protein log2 Fold-Change

**C.**

Condition

| Condition | | Cluster | | Protein expression (log2FC) |
|---|---|---|---|---|
| RPMI | *C. albicans* | Cluster 4 | | -4 -2 0 2 4 |
| LPS | Poly(I:C) | Other | | |
| *S. aureus* | | | | |

Protein expression

DE   Non-DE