Human alveolar macrophage response to *Mycobacterium tuberculosis*:

immune characteristics underlying large inter-individual variability

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Abstract

Mycobacterium tuberculosis (*M.tb)* establishes residence and growth in human alveolar macrophages (AMs). Large inter-individual variation in *M.tb*-AM interactions is a potential early indicator of TB risk and efficacy of therapies and vaccines. Herein, we systematically analyze interactions of a virulent *M.tb* strain with freshly isolated human AMs from 28 healthy adult donors, measuring host RNA expression and secreted candidate proteins associated with TB pathogenesis over 72h. We observe large inter-individual differences in bacterial uptake and growth, with tenfold variation in *M.tb* load at 72h, reflected by large variation of gene expression programs. Systems analysis of differential and variable RNA and protein expression identifies TB-associated genes and networks (*e.g.*, *IL1B* and *IDO1*). RNA time profiles document early stimulation of M1-type macrophage gene expression followed by emergence of an M2-type profile. The fine-scale resolution of this work enables the separation of genes and networks regulating early *M.tb* growth dynamics, and development of potential markers of individual susceptibility to *M.tb* infection and response to therapies.

Introduction

One-quarter of the world's population is approximated to be infected with *Mycobacterium tuberculosis* (*M.tb)*, and nearly 1.3 million people die annually from tuberculosis (TB), a continuing worldwide public health problem(WHO, 2020). While a substantial portion of the human population gets infected with *M.tb*, only a fraction of infected individuals progress to active TB. To control TB, we must understand the immunopathogenesis of *M.tb* infection, including host susceptibility or resistance

factors, to develop effective diagnostic, therapeutic and vaccine strategies for different

individuals and populations(Azad et al., 2020).

Aerosolized *M.tb* enters the lung alveolar space where it is phagocytosed by alveolar

macrophages (AMs), unique resident cells with a complex immunologic profile, to

become an intracellular pathogen. *M.tb* infection activates several macrophage

immunobiological pathways, including those involved in phagocytosis, phagosome-

lysosome trafficking, and triggering of inflammatory cytokines, oxidants, and cell

death pathways – all processes of innate immunity. Yet, critical factors that dictate

M.tb infection and progression to TB remain uncertain - a roadblock to understanding

an individual's susceptibility to TB(Guirado et al., 2013, Rajaram et al., 2014, Schorey

and Schlesinger, 2016).

The host response to *M.tb* infection ranges from complete clearance of infection to

latent infection to active TB(Pai et al., 2016). Therapy and vaccine trials further

highlight response variability across populations(Azad et al., 2020, Finan et al., 2008)

with BCG vaccination trials attaining only 50% efficacy(Colditz et al., 1994).

Evolutionary adaptation of *M.tb* to the host is considered a main factor modulating

virulence, host response, and TB severity(Sousa et al., 2020, Liu et al., 2017). For

example, evasion of immune surveillance by suppression of IL1B was proposed to be

largely dictated by virulence of the *M.tb* strain(Sousa et al., 2020); however,

expression of differentially expressed (DE) genes during infection with a single *M.tb*

strain can vary >10-fold between individuals(Azad et al., 2013). Therefore, both

genetic(Azad et al., 2012) and environmental/epigenetic(Thuong et al., 2008, Barreiro

et al., 2012, Moores et al., 2017, Rajaram et al., 2011) host factors also play a role,

while being less well understood.

Heritability estimates of susceptibility to TB range from 80% (twin and population

studies) to 25-50% polygenic risk scores(Naranbhai, 2016); yet, GWAS-significant

genetic variants alone fail to account for most of the estimated heritability(Naranbhai,

2016, Uren et al., 2017). Both *in vitro* and *in vivo* transcriptome studies of *M.tb*-

infected macrophages and other immune cells reveal DE candidate genes(Lavalett et

al., 2017, Roy et al., 2018, Rothchild et al., 2019, Moreira-Teixeira et al., 2020),

resulting in gene networks (Rajaram et al., 2014, Barreiro et al., 2012, Blischak et al.,

2015, Wu et al., 2014, Bragina et al., 2016), including type I IFN-associated

signatures in active TB(Moreira-Teixeira et al., 2020). Similarly, protein studies invoke

factors associated with TB status, including indoleamine oxidase 1 (IDO1), a marker

of active TB(Adu-Gyamfi et al., 2017). Complexity of these interacting processes

confound predictions of individual TB risk.

Our study addresses a critical gap in the field, the poorly understood variation of host

innate immune responses between individuals during *M.tb* infection, by characterizing

immune response genes and pathways that differ between individuals during infection

of human AMs from healthy donors with a single virulent *M.tb* strain. We identify host

genes and functional networks with highly variable expression between AM donors

correlating with *M.tb* growth dynamics in AMs, some already recognized as potential

biomarkers of active TB(Adu-Gyamfi et al., 2017, Gautam et al., 2018, Zak et al.,

2016, Moreira-Teixeira et al., 2020, Sousa et al., 2020).

Results

Heterogeneity in *M.tb* uptake, adaptation and growth in human AMs among

donors

We infected human AMs from 28 adult healthy donors over 2h with a virulent *M.tb*

strain ($H_{37}R_v$) engineered to emit light (luminescence RLU values), and followed RLUs

over 72h (**Figure 1A,B**). After batch effect correction, large variations in RLU values

are detectable at each time point (**Figure 1B; Supplementary File 1**). RLUs correlate

with *M.tb* colony forming units (CFUs), jointly reflecting the number of intracellular

bacilli and microbial metabolic activity(Salunke et al., 2015), while early RLU levels at

2-24h post-infection largely reflect *M.tb* cellular uptake and early intracellular

adaptation. AMs with the highest and lowest RLUs display a nearly tenfold difference

at 72h. *M.tb* growth rates (24-72h post infection) are consistent with the expected

M.tb doubling time (here referred to as generation time, in minutes required for

doubling over 48-72h post infection), while varying 2-3 fold between donors. The

assays presented throughout were conducted at a multiplicity of infection (MOI) of 2:1

(*M.tb*/AM cells). Bacterial growth rates (24-72h) were similar using a MOI of 10:1

(**Supplementary File 1**). To identify proteins and genes that influence *M.tb*-AM

interactions, we focus on generation times (48-72h) in this study, since RLU levels

prior to 48h post infection reflect *M.tb* uptake, adaptation, and early growth combined.

Human AM-secreted proteins capture the immune response to *M.tb* infection

To assess the inflammatory mediator response by macrophages to *M.tb* infection, we

measured 27 secreted proteins, previously implicated in cellular responses to *M.tb*

Figure 1. Panel A. **Schematic of *M.tb* cell adhesion and uptake, adaptation and growth in human alveolar macrophages (AMs)**. **Panel B**. Changes in normalized luminescence RLU values over the course of *M.tb* infection. The x-axis shows hours post infection, with RLUs representing mostly uptake and adaptation at 2h and 24h, and growth rates (72h/48h) (data in Supplemental Table 2; results shown here are with MOI 2:1). **Panels C, D,** and **E**. Differentially secreted proteins post infection at 2, 24, and 72h respectively (infected/controls at each time point). The bars represent adjusted p values (-log10), with significant proteins shown with black bars. **Panels F, G,** and **H**. Correlations (R^2) between protein levels and *M.tb* generation time (time for doubling during 48 to 72h period). Positive R^2 values indicate that increased levels correlate with increased generation times, and *vice versa.*

Figure supplement 1. The transcriptional response of 28 human AM cultures to *in vitro* incubation and to *M.tb* infection.

infection, in all AMs over 72h (**Supplementary File 2**). At 2h, 6 of the 27 proteins

(22.2%) are significantly differentially produced after *M.tb* infection (**Figure 1C**),

increasing to 23 proteins (85.2%) at 72h (**Figure 1E**), all with increased secretion in

infected cells. Differential secretion varies over time, with IL6 and MMP2 displaying

highest levels at 2h, and IL6, CCL13, and CCL3 at 72h. Pronounced *M.tb*-stimulated

secretion of MMP2 only at 2h (without stimulated mRNA expression; not shown)

suggests a mechanism of rapid release from the cell rather than *de novo* transcription.

Pro-inflammatory mediators including IL1β, TNF, and IL6 display significant differential

secretion at all-time points, indicating their contribution to a pro-inflammatory reaction

to infection.

We then tested whether protein levels secreted from infected cells correlate with *M.tb*

generation times (**Figure 1F-H; Supplementary File 3**), with Pearson correlation

reaching r=0.57 (IL7 at 2h). Three proteins are significant (FDR adj. p values <0.05):

IL7 (2h, 72h), IL10 (2h, 24h), and MMP10 (24h). High IL10 levels correlate with longer

generation times (slower growth) (r=0.46 and 0.49 at 2 and 24h, respectively),

whereas IL7 has a positive r value (0.57) at 2h and a negative one (-0.41) at 72h (but

is present at only low levels). A similar trend occurs with MMP10. Opposite effects at

different time points highlight the changing *M.tb*-AM interactions occurring over time.

These results indicate that protein expression profiles over the first 3 days of infection

influence *M.tb*-AM interaction dynamics.

Transcriptomes of uninfected control and *M.tb*-infected human AMs reveal

differentially expressed gene profiles

Transcript profiles were assessed for each AM sample at 2, 24, and 72h post infection,

using AmpliSeq(Papp et al., 2018). At each time point, 10,000-14,000 mRNAs were

detectable, and reads per million (RPM) from replicate assays were highly correlated

($r^2 \geq 0.99$), enabling sensitive detection of differentially expressed (DE) genes. A

principal component analysis (PCA) of all datasets from control and infected AMs

reveals that 52% of the variance in gene expression between time points resulted from

exposure to *ex vivo* culture conditions alone, while *M.tb*-induced RNA expression

changes are smaller but increase over time (**Figure 1 - figure supplement 1**).

To identify significant DE genes (FDR adjusted $p \leq 0.05$) specific to infection, we

analyzed RNA expression by comparing uninfected control cells to infected cells at

each time point(Papp et al., 2018). This yielded 62 DE genes at 2h, 2,177 at 24h, and

3,662 at 72h post infection (**Figure 2A**; **Supplementary File 4)**. Thirty-six DE genes

significant at all-time points (**Figure 3**) include those encoding inflammatory cytokines

(IL1A, IL1B, TNF) and chemokine receptors (*e.g.*, CCR7) characteristic of a spectrum

representing "M1 type" cell states. Gene set enrichment analysis of 72h DE gene

profiles, using gene co-expression modules previously identified during macrophage

differentiation(Xue et al., 2014), shows significant enrichment of M1-like modules

(**Figure 2B**). An independent assignment of M1- and M2-associated genes(Orecchioni

et al., 2019) reveals high overlap of DE genes at each time point with either M1 or M2

genes (**Figure 2C-F**), accounting for 44.0% of M1 genes and 34.0% of M2 DE genes

at 72h. Cell type deconvolution with Quantiseq on the RNAseq profiles(Finotello et al.,

2019) supports a strong shift to M1 macrophages in infected samples, peaking at 24h,

whereas the M2 cell type predominates at 72h in control AMs (**Figure 4A,B**). While

significant correlations between M1/M2 profiles and *M.tb* uptake/growth dynamics are

Figure 2. The transcriptional response of 28 human AMs to *M.tb* infection. **Panel A**. Venn diagram of differentially expressed (DE) genes between *M.tb*-treated and controls at three time points. Total number of genes with detectable expression (≥1RPM) was ~12,000. DE genes were detected with DESeq2 (adjusted p values <0.05): 62 at 2h, 2,177 at 24h, and 3,662 at 72h, with overlaps displayed in the Venn diagram. **Panel B.** Gene set enrichment analysis of DE genes from 72h using 48 gene expression modules previously determined as operational in macrophage differentiation. Modules annotated as 'M1-like' or 'M2-like' are shown in blue and red. **Panel C.** The number of DE genes with >2-fold upregulation defined as 'M1-like' or 'M2-like'. This uses an independent definition of M1-like and M2-like genes to (B). **Pane D-F:** Log$_2$ fold change and log$_2$ average expression for DE genes at 2h (D), 24h (E) and 72h (F). M1 and M2 genes are shown in blue and red respectively.

161   not detectable, individual donors vary significantly in the expression of several

162   characteristic M1 or M2 genes (**Figure 5**). As one example, STAT1 (a transcription

163   factor determining M1-like state) is one of the most differentially expressed genes

164   between infected and control macrophages at both 24h and 72h with an average of

Figure 3. **The transcriptional response of 28 human AMs to *M.tb* infection.** Shown are the 36 significant DE genes common to all time points (see Figure 2A), and their log$_2$ fold change.

165   >4-fold induction of gene expression over 72h, though induction varies between AM

166   donors from a 2-fold reduction to a 25-fold increase.

Figure 4. Cell type deconvolution with Quantiseq on RNAseq profiles at 2, 24 and 72h in infected and control cells. Panel A. Distribution of cell types visualized by the color code shown below. Note the preponderance of M1 type cells at 24h infected AMs, and of M2 type cells at 72h in controls. **Panel B.** Boxplots showing the proportion of M1 (left) and M2 (center) cells in infected and control cells at each time point, on the right is the legend for cell type proportions for the bar plots in (A).

169   Differentially expressed genes (DE genes) displaying the most variable

170   expression among individual AMs (VE genes)

Figure 5. mRNA expression profiles over 72h in uninfected control and *M.tb*-infected AMs. The selected genes are marked as belonging to the M1 or M2 type macrophages, as annotated by other groups (Viola et al. 2019; Li et al. 2021), being involved in key metabolic differences between M1 and M2 types (categories: Transcription Factor, Surface Marker, Released Cytokine or Metabolic Enzyme, and sub categories such as M2A/M2B/M2C or OXPHOS/GLYCO.). https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6618143/). See **Supplementary File 10.**

Genes with the most robust variable expression are of particular interest in

understanding inter-subject differences. We performed variance analysis of gene

expression in both control and infected AMs at all-time points, yielding a set of 324

genes with highly variable expression (VE genes; **Supplementary File 5A**). All 324 VE

genes are specific to the infected AMs, upregulated in infected cells, and also significant

DE genes (VE/DE genes). Examples include *IFI6, IL1B, CCL4, IDO1, GBP5, IRF1,*

JAK3, UBD, CXCL,5, CCL20, VDR, CD80, IFI44L, NLRP3, and *IL7R,* several of which

were previously implicated in TB pathogenesis. Correlations between expression of

these genes with *M.tb* generation times are listed in **Supplementary File 5A**. Several

genes (in RPMs) have strong correlations (r) with generation times, *e.g., MICAL2* (-0.69

at 24h), *RASSF2* (-0.73), *CD180* (-0.51), and *CNP* (0.49), the strongest correlations

associated with shortened generations times.

The extent of variable expression of the VE/DE genes is exemplified by the RNA

profiles across the 28 AMs (**Figure 6**). Among the VE/DE genes, expression of IDO1

mRNA is substantially stimulated by *M.tb* in only 10 of the 28 donor AMs (**Figure 6A**).

IL1B is more broadly expressed, but with high expression mostly coinciding with high

IDO1 expression (**Figure 6A**), similar to several other key genes (*e.g.*, IFNG, CXCL10,

UBD, IFI44L; **Figure 6B**). These most variably expressed VE/DE genes are likely

relevant to inter-individual variability following infection of AMs.

Reactome analysis yields several significant pathways, including Immunological

Diseases/Cellular Function and Maintenance/Inflammatory Response, and

Function/Immune Cell Trafficking (**Supplementary File 5B**). Ingenuity Pathway

Analysis (IPA) of the VE/DE genes yields the highest scoring hierarchical network with

Figure 6. Expression of *IDO1*, *IL1B*, and co-expressed genes in AMs infected with *M.tb* over 72h. Panel A. Expression of *IDO1* and *IL1B*. Both are variably expressed with a different pattern across the 28 AMs. **Panel B**. Select mRNA transcripts with co-expression patterns similar to *IDO1*. *IDO1* is poorly expressed in 18 of 28 AMs (A), with tightly co-expressed genes representing the most variably expressed gene cluster (B).

197   IL1B at the top, and with STAT1, IRF1, and IDO1 as connected nodes (**Fig. 7,** full gene

198   annotation in **Figure 7 – figure supplement 1)**. Both *STAT1* and *IRF1* interact with the

199   *IDO1* promoter(Xue et al., 2012).

Figure 7. Network of DE genes with highly variable RNA expression (VE/DE genes). These VE/DE genes (n=324) were identified in the 28 AMs after *M.tb* infection across all time points. Standard pathway enrichment program, Ingenuity Pathway Analysis (IPA) (https://www.qiagenbioinformatics.com/products/ingenuity-pathway-analysis/), generates a top scoring gene network with *IL1B*, *UBD*, *STAT1*, and *IRF1* as key hub genes. *STAT1* and *IRF1* cooperatively bind to the promoter of *IDO1*, which is also highlighted (fully annotated network is depicted in Figure 7 – figure supplement 1). These key gene names are highlighted in red.

Figure supplement 1. Top scoring network of DE genes with highly variable expression (VE/DE genes).

Identification of human AM genes associated with *M.tb* growth

Single RNA profiles across the 28 donor AMs display high correlations with *M.tb* growth dynamics but fail to yield significance upon FDR corrections. Several candidate genes strongly correlate between RPMs at 24h and generation time, suggesting biologically relevant relationships. To explore this further, we tested correlations between *M.tb* generation times and gene expression modules, using WGCNA to build three consensus networks using batch-corrected RNA profiles from infected and control cells at 2, 24 and 72h, with RNAs having RPMs >35. This approach yielded 9,193, 9,098 and 9,115 genes, and identified 26, 27, and 37 modules for the 2, 24 and 72h time points, respectively (**Supplementary File 6A**). Correlation between network eigengene modules for infected cells and *M.tb* generation times (during 48-72h) at 2, 24 and 72h identified four significant associations between bacterial growth rate and eigengene modules, all in the 24h network (FDR-corrected p-value <0.05; blue r=-0.52, yellow r=-0.61, red r=-0.55 and tan r=0.52; **Supplementary File 7,** columns D,E, modules highlighted in red**)**. Reactome pathway over-enrichment analysis (**Supplementary File 8**) showed Processing and Metabolism of RNA, and DNA Damage/Repair as significantly associated with these gene modules. Regulation of genes involved in DNA repair and recombination had been linked to *M.tb* regrowth from its non-replicating, persistent state(Du et al., 2016). This result supports a nexus between gene networks and *M.tb* generation times.

To prioritize genes within significantly associated modules, we measured correlations between generation time and gene expression for each gene within the four significant modules (**Supplementary File 6B**, columns Q-V). We lowered the stringency of our

approach by performing multiple test correction based upon the module size, rather

than for all expressed genes. This approach yielded 143 significant genes, with 139

genes belonging to the yellow module in the 24h network (97.2%). The yellow module

genes have mostly negative correlations with generation times (117 of 139 genes,

84.2%); *i.e.,* elevated expression of these genes is associated with shorter generation

times (higher growth rates), perhaps signaling a key *M.tb*-induced AM response

favoring bacterial growth.

We performed hierarchical clustering of gene expression profiles and AM donors for

genes within the yellow module, limiting to genes where we find a significant correlation

between generation time and expression level (**Figure 8A**). This revealed four groups of

genes, two of which contain genes with a positive correlation to generation time

(clusters I and II), and two with a negative correlation to generation time (clusters III and

IV). Hierarchical clustering also identifies three groups of AM donors, groups 1 and 2

have significantly longer generation times compared to group 3 (**Figure 8B**)

Gene expression sub-groups display opposite profiles between groups 1 and 3, with

group 2 in between. We performed KEGG pathway enrichment of gene expression

clusters I and II (positively correlated with generation time) and clusters III and IV

(negatively correlated with generation time). This identified the TNF signaling pathway

as significantly enriched in negatively correlated genes (**Figure 8D**), and oxidative

phosphorylation and thermogenesis significantly enriched in positively correlated genes

(Figure 8E). These results further support a biological relationship between gene

expression profiles and *M.tb* generation times.

Figure 8. Association of the yellow gene module from 24h samples with generation time. (**A**) Gene expression profile of 139 genes from the yellow module which are correlated with generation time. Each gene is Z-normalized across all samples for ease of presentation (Expression). To the right of the heatmap is the generation time for each sample (Generation Time), and a dendrogram capturing the distance between samples. Below the heatmap are the r values for gene expression against generation time. Above the heatmap is a dendrogram capturing the distance between gene expression profiles. Three clusters of individuals were identified from the gene expression data (1-3). (**B**) The boxplot displays the generation time for individuals within each cluster; both cluster 1 and cluster 2 have significantly higher generation times than cluster 3. (**C**) The boxplot shows the distribution of r^2 values for all modules from 24h expression data. (**D**) KEGG pathway enrichment for negatively correlated genes (clusters III and IV). (**E**) KEGG pathway enrichment for positively correlated genes (clusters I and II).

Transcriptional modules coordinating the secreted protein response to *M.tb*

infection in human AMs

Among the measured proteins implicated in TB pathogenesis, IL7, IL10 and MMP10

are significantly correlated with bacterial growth (Figure 1). In addition, the other

measured proteins have also been shown to impact disease progression through

interactions with the immune system not captured in our *in vitro* system. To identify the

transcriptional modules that may regulate or respond to these proteins, we assessed

correlations between eigengene modules and secreted protein levels (**Supplementary**

File 9), identifying 29 significant correlations after Bonferroni correction. Only 6/29

significant correlations are in non-infected control AMs, 3 of which are at the 2h time

point where there is little divergence in gene expression between control and infected

conditions. Of these, CCL3 expression is strongly correlated with the royal blue

module [**Supplementary Files 8** (column b) **and 9**], suggesting that the preexisting

expression profile in non-infected AMs may affect *M.tb* generation times.

In the 24h network, we find three modules with a significant link to both growth rate

and protein expression **(Supplementary Files 6B and 7)**. These are CCL3 (blue, red

and yellow modules) and IL10 (red module). Significant correlations between these

gene modules and individual proteins also suggest a causative relationship between

gene expression and *M.tb* growth.

At 72h, a single gene expression module (tan) correlates with the expression of

multiple proteins (IL15, IL18, IL1A and TNF). This module overlaps substantially with

our highest scoring network from IPA analysis of variably expressed VE/DE genes

(**Figure 7 – figure supplement 1**) with 47 of 184 module eigengenes (25.4%) falling

within this network, including *IDO1*, *IL1A* and *IL1B.*

Discussion

This study confirms large inter-individual variation in interactions between human AMs and a single virulent strain of *M.tb* (Figures 1 and 2), and for the first time dissects biological mechanisms underlying individual differences. Sousa et al.(Sousa et al., 2020) had demonstrated that secretion of IL1B is a surrogate marker distinguishing between TB cases with mild disease and severe TB, attributing differences in IL1B induction to virulence of the strains tested, independent of the host. However, here we show that a single virulent *M.tb* strain elicits substantial differences in IL1B expression between individual AMs, highlighting host factors, with IL1B one possible predictive marker of TB susceptibility.

The nexus between secreted TB candidate proteins and eigengene modules further supports the finding that gene expression networks, both in uninfected and *M.tb*-infected cells, affect early *M.tb*-AM interactions. While we have applied stringent FDR adjustments to reveal significant correlations, strong candidate genes and networks can serve to extract a deeper understanding of the various phases of *M.tb*-AM interactions and their possible significance in the pathogenesis of TB.

We first measured 27 candidate proteins that are secreted by *M.tb*-infected AMs and uninfected controls, finding robust stimulation by *M.tb* and inter-subject differences (Figure 1 C-H). Importantly, three proteins (IL7, IL10, and MMP10) are significantly correlated with bacterial growth over 48-72h (Supplementary File 3), supporting the hypothesis that proteins relevant to TB pathogenesis affect early *M.tb*-AM interactions, possibly presaging individual susceptibility to TB.

RNA expression profiles also appear to reflect or influence *M.tb*-AM interactions. The

precision of the AmpliSeq RNA assay, together with use of control AM expression at

each time point(Papp et al., 2018), enabled sensitive detection of numerous DE RNAs

across the 28 AMs (Figure 2; Supplementary File 4). DE genes significant at each time

point (Fig. 3) are consistent with previously reported results (*e.g.,* (Papp et al., 2018,

Zak et al., 2016, Moreira-Teixeira et al., 2020)), including inflammatory cytokines CSF2,

IL6, IL1B, and IFNG, but also anti-inflammatory factors such as CCL22. Gene Ontogeny

(GO) Pathway analysis reveals the expected prevalence for Innate Immune System,

Cytokine Signaling in Immune System, and more. The DE genes include both a

classically activated M1 type induced by inflammatory agents (*e.g.,* IFNG) and

alternatively activated M2 type induced by IL4 and IL13(Roy et al., 2018). While M1 and

M2 markers vary between individuals, the M1 type is strongly activated at 24h post

infection, while M2 markers increase at 72h, in particular in the uninfected cells (Figure

4). The balance of this mixed mode of activation may account in part for inter-subject

differences in *M.tb*-AM interactions, but no significant trends are observed. In previous

reports, *M.tb* ESAT-6-induced macrophage polarization to M1 phenotype occurred

early, then switching to M2 phenotype at a later stage of infection(Refai et al., 2018). In

our study, a substantial switch to the M2 phenotype at a later stage (72h) was observed

in uninfected control macrophages compared to infected AMs, which could be due to

increased expression of MMPs in control cultures. Upregulation of certain MMPs was

found to be associated with macrophage polarization to both M1 and M2 phenotypes in

M.tb-infected, cigarette smoke-exposed macrophages(Le et al., 2020).

Among the gene co-expression modules, one (yellow) significantly correlates with *M.tb*

generation times and, in addition, contains numerous individual genes that also

significantly correlate with *M.tb* growth (Supplementary File 6). As most correlations are

negative, these genes appear to favor *M.tb* growth. The module GO terms indicate

influence over translation processes, a potential mechanism by which *M.tb* usurps the

cellular machinery to its advantage.

Variably expressed (VE) genes can reveal markers of individual susceptibility or

resistance to disease phenotypes(Li et al., 2018), tested here for *M.tb* infection of AMs.

We find that all of the most robust VE genes also classify as DE genes, likely

contributing to the fate of *M.tb* in the cells. Prominent examples of VE/DE genes encode

IL1B and IDO1 (Supplementary File 5), suggesting that VE/DE genes are relevant to

infection and disease progression. IPA analysis of VE/DE genes yields Interferon

Signaling as the top pathway, and a network with IL1B, STAT1, and IRF1 as dominant

hubs including genes previously implicated in the cellular response to *M.tb* (e.g.,(Zak et

al., 2016, Moreira-Teixeira et al., 2020, Rothchild et al., 2019)) (Figure 7; Figure 7 –

figure supplement 1). This IL1B-dominated network connects IL1B, STAT1, and IRF1 to

IDO1, consistent with previous reports that the IRF1/STAT1 transcription complex binds

to the *IDO1* promoter(Xue et al., 2012, Du et al., 2000). IDO1 has been proposed

recently as a sensitive and selective biomarker for active TB(Adu-Gyamfi et al., 2017).

Its metabolic products, immunosuppressive kynurenins, act by preventing access of

cytotoxic T cells to infected macrophages in TB lung granulomas(Gautam et al., 2018).

IDO1 is robustly expressed in only 10 of 28 AMs after *M.tb* stimulation, with a similar

expression profile for IL1B, CXCL9-11, IFNG, UBD, IFI44L, and GBP5 (an IFN/IL1B

activated GTPase mediating antibacterial defense) (Figure 6). We propose that

expression of both IL1B and IDO1 could be early predictive biomarkers of susceptibility

to *M.tb* for a given individual.

The nexus we observe between secreted proteins reported relevant to TB and gene

expression modules, with overlap to variably expressed VE/DE genes and, on the other

hand, to *M.tb* generation times, strengthens our hypothesis that early *M.tb*-AM

interactions could signal an individual's susceptibility to infection and potentially risk of

overt TB.

In summary, our results identify known and novel key genes and their encoded

transcripts and proteins in the early phase of *M.tb* infection of freshly isolated human

AMs. Previous work shows that infection of macrophages with *M.tb* stimulates multiple

pathways, including both interferon type 1 and 2 pathways – thought to exert opposing

effects on infections(Roy et al., 2018, Rothchild et al., 2019). We show here that

variably and differentially expressed genes and their networks affecting *M.tb*-AM

interactions can account for inter-individual variability during the early phase of infection.

Results of this study provide a foundation for identifying predictive biomarkers of an

individual's susceptibility or resistance to *M.tb* infection, and response to vaccines and

therapeutics(Tameris et al., 2013).

Limitations. While the study group of 28 healthy AM donors was sufficient to reveal

significant genes associated with *M.tb*-AM interactions, our results require replication.

Larger cohorts will be needed to address contributions of single genes and networks to

uptake, adaptation, and growth, reveal genetic factors, and assess ethnicity, sex and

age, and environmental factors. Nevertheless, the study approach provides rich

datasets suitable to accelerating the development of predictive biomarker panels of an

individual's risk for TB. The design of our study precluded repeat measures from each

donor. However, our longstanding studies with healthy donor human monocyte-derived

macrophages has demonstrated that individual donors provide consistent results for

comparable measurements over time.

Materials and Methods

Measurements of uptake, adaptation, and growth rate of *M.tb* in infected AMs

Fresh AMs were obtained within 6h from 28 tuberculin skin test (TST)-negative

healthy donors from Caucasians, Asians, Africans, according to the demographics of

the Columbus, Ohio area (**Table 1**), under an approved IRB protocol at the Ohio State

University Wexner Medical Center. Isolation and culture of human AMs from

bronchoalveolar lavage (BAL) was done as described(Gaynor et al., 1995, Nguyen et

al., 2012). Briefly, BAL fluid was centrifuged and washed once in cold RPMI at 4^0C,

and the cell pellet was re-suspended in RPMI medium. A portion of the cell

suspension was subjected to cytospin followed by staining and microscopy to

determine macrophage content (94 ± 5%; mean ± SD, N=10). AMs were adhered in

either a 24-well plate (1.5×10^5 cells/well) or 96-well plate (5×10^4 cells/well) in RPMI

containing 10% human AB serum and Penicillin G (10,000 U/ml) for 2h (99% pure)

before collecting the supernatants and washing/lysing the adhered cell monolayer, in

part used for protein and RNA analysis, respectively. Then, medium was replaced

and incubations continued until 24 and 72h to repeat protein and RNA analysis.

Table 1. Donor demographics of AM samples used in this study (n=28)

Donor	Sex	Age (Years)	Race	Donor	Sex	Age (Years)	Race
D1	Female	24	Asian (Chinese)	D15	Male	18	Hispanic
D2	Male	24	African-American	D16	Female	25	Caucasian
D3	Male	27	Caucasian	D17	Female	20	Caucasian
D4	Female	26	Caucasian	D18	Female	26	Caucasian
D5	Female	26	Caucasian	D19	Male	19	African-American
D6	Male	21	Caucasian	D20	Female	22	Hispanic
D7	Male	24	Caucasian	D21	Male	20	Asian (Chinese)
D8	Female	22	Caucasian	D22	Female	19	Not stated
D9	Male	23	Caucasian	D23	Female	19	Caucasian
D10	Male	21	Caucasian	D24	Male	23	Caucasian
D11	Female	46	Caucasian	D25	Male	24	Hispanic
D12	Female	22	African-American	D26	Male	23	Caucasian
D13	Male	27	Asian (Indian)	D27	Female	20	Caucasian
D14	Male	33	Asian (Chinese)	D28	Female	19	Caucasian

Male/Female = 14/14; Caucasian = 60% (17/28), Asian = 14% (4/28), African-American = 11% (3/28), Hispanic = 11% (3/28)

Virulent *M.tb* $H_{37}R_v$ single cell suspensions were prepared(Schlesinger et al., 1990).

The virulent *M.tb* strain used contains the entire bacterial Lux operon cloned in a

mycobacterial integrative expression vector (*M.tb* $H_{37}R_v$-Lux) as described(Salunke et

al., 2015). *M.tb* cellular uptake, adaptation, and intracellular growth were assessed as

relative luminescence units (RLUs) at 2, 24, 48, and 72h in 3-5 wells for each

condition (mean values of 3-5 technical replicates are provided for each donor) using

a multiwell plate reader Glomax (Promega). Each 2h incubation was performed at a

multiplicity of infection (MOI) of both 2:1 and 10:1 (*M.tb/*AM cells for RLU assays);

RNA and protein was measured only with MOI of 2:1.

For technical reasons, AM uptake and growth assays from donors 1-16 were

incubated in 24 well plates, while AMs from donors 17-28 were incubated in 96 well

plates. Use of the different plates resulted in ~3-fold difference in mean RLUs

between the two sets of donor groups (directly related to a different number of

AMs/well). For all analysis we performed batch correction of protein, transcript and

growth rate measures using ComBAT(Johnson et al., 2007) to remove the impact of

different plates used during culture as such we specified the batches as individuals 1-

16 and 17-28.

Measurement of secreted proteins in control and *M.tb*-infected AMs

Supernatants from culture wells of uninfected and infected AMs from 28 donors at 2,

24, and 72h were analyzed for secreted proteins relevant to *M.tb*-macrophage

interactions using multiplex kits from Meso Scale Discovery (MSD) (Rockville, MD).

The supernatants were collected at 2h and replaced with fresh medium, followed by

continuing incubation until 24 or 72h. Twenty-seven secreted proteins were

measured: 4 inflammatory mediators (TNF-α, IL-6, IL-1β, IL-10; V-PLEX kit), 6

cytokines [CSF2 (GM-CSF), IL-15, IL-16, IL-1α, IL-7, VEGFA] and 12 chemokines [IP-

10 (CXCL10), MCP-1 (CCL2), MCP-4 (CCL13), MDC (CCL22), IL-8, TARC (CCL17),

MIP-1α (CCL3; U-PLEX (customized multiplexing), MIP-1β (CCL4), ENA-78 (CXCL5),

IL-18, MIP-3α (CCL20), MIP-3β (CCL19)], and 5 matrix metallo-proteinases (MMP-1,

MMP-2, MMP-3, MMP-9, MMP-10; MMP 3-PLEX and MMP 2-PLEX).

Measurement of RNA expression from uninfected and *M.tb*-infected human AMs

Expression of 20,804 RNAs, including 2,228 non-coding RNAs (ncRNAs), was

measured with AmpliSeqTM (Whole transcriptome Human Gene Expression Kit, Life

Technologies) for 28 donor AMs at 2, 24, and 72h after infection, for both uninfected

controls and infected AMs at each time point (MOI 2:1). AmpliSeq transcriptome

analysis incorporates a targeted, amplicon-based (~110 bps, spanning exons)

workflow, and is quantitative over orders of magnitude. The precision of AmpliSeq

analysis detects *M.tb*-induced expression changes with high sensitivity in human

MDMs and AMs infected with *M.tb*(Papp et al., 2018). Genomic DNA and total RNA

(TRIzol® Reagent (Ambion™, Austin, TX)) were prepared from AMs using published

procedures(Azad et al., 2013). RNA was purified, DNase-treated, RNA concentration

measured, and RNA integrity assessed as described(Papp et al., 2018). After reverse

transcription of 10 ng total RNA, using the AmpliSeq primers with the SuperScript®

VILO™ cDNA Synthesis kit. the cDNAs were amplified for 12 cycles with Ion

AmpliSeq™ primers and barcoded adapters, resulting libraries purified and pooled in

equal amounts for emulsion PCR on an Ion OneTouch™ 2 instrument, followed by

sequencing with the Ion Proton™ sequencer(Papp et al., 2018). Reads were aligned

to BED (Browser Extensible Data) file specific for AmpliSeq amplicons. Typically, we

obtain 5-9 million mappable reads per sample, with ~50-60% of RNA targets

detected(Papp et al., 2018). Repeat experiments in the same sample yield correlation

values of r^2>0.99 (for both independent replicates and sequencing chip replicates).

The AM sample from D17 at 2h and 72h yielded <1 million reads and were excluded

from the analyses. The AmpliSeq reads were normalized to mapped fragments per

million reads for quantifying transcript expression levels(Mortazavi et al., 2008),

yielding relative abundance for predicted transcripts in each AM.

Differentially-expressed (DE) genes between control and *M.tb*-infected human

AMs

To identify DE genes, we employed DESeq2(Love et al., 2014). FDR adjusted p

values of 0.05 were used as cutoff for identifying DE genes at each time point. We

estimated size factors using the "poscount" approach to correct for different

sequencing depth and performed independent analysis at each time point, specifying

the individual/donor and condition (infected or control) in the model.

Weighted gene co-expression network analysis) (WGCNA)

We derived three gene co-expression works using WGCNA(Langfelder and Horvath,

2008) with the following parameters; power=8, TOMtype=signed, minModuleSize=30,

mergeCutHeight=0.25, minKMEtoStay=0. These were blockwise consensus modules

with the gene expression data from the control and infected cells grouped

independently. We correlated the module eigengenes to either bacterial growth rate, or

to proteins expressed/secreted from the same time point and performed FDR correction

on p values.

Detection of genes with variable expression in control and *M.tb*-infected AMs,

characterized by variance measures

To identify the most variably expressed RNAs in control AMs and in those separately

after *M.tb* infection, all AM transcriptome data at each time were subjected to Levene's

test(Levene, 1960), with ratios of variances as test statistics, reported adjusted p-value

(FDR) for selected RNAs. A second variability test assesses whether the entropy of a

given RNA's expression is higher than expected given the total entropy in the *M.tb*-

treated AMs(Handelman et al., 2015). A permutation test yields p-values for significance

of the entropy computations.

Gene pathway and ontogeny analysis. We performed over representation analysis of

gene ontology (GO) terms and reactome pathways using WebGestalt(Liao et al., 2019)

taking the relevant gene lists for each comparison as an input and using default

parameters. We retained GO terms or pathways which reached an FDR corrected p

value of 0.05. Comparison to genes associated with M1 and M2 states was performed

using a curated list of genes from Viola et al.(Viola et al., 2019) and Li et al.(Li et al.,

2021).

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Competing Interests

The authors declare no competing interests.

Supplementary Files:

Supplementary File 1. Relative *M.tb* Luminescence Units (RLUs) and RLU ratios

between time points. All 28 AMs were incubated for 2h with *M.tb* at MOI 2:1 and 10:1,

and luminescence was measured at 2, 24, 48, and 72h (n=3 per sample and time

point). The RLU profiles were similar between MOI 2:1 and 10:1; therefore, only MOI

2:1 values are shown. To estimate *M.tb* generation times (equivalent to growth rates)

between 24, 48, and 72h, RLU ratios between time points were calculated with

unadjusted RLUs, yielding similar results with MOI 2:1 and 10:1, indicating the ratios are

robust and reproducible.

Supplementary File 2. Protein (n=27) levels secreted into the culture medium

during 2, 24, and 72h incubation of uninfected AMs (Con) and after infection with

***M.tb* (Mtb) from 0-2h incubation.** The incubation medium was changed once at 2h.

Results are in picogram/ml, secreted into the medium by AMs over the incubation

periods 0-2h, 2-24h, and 2-72h. Each value is the mean of results from duplicates of

each of 2 independent samples per AM*.*

Supplementary File 3. Correlations between secreted proteins and *M.tb*

generation time during the 48 to 72h incubation period. All values are r correlations,

with + or – indicating whether the correlation is positive (longer generation time) or

negative (shorter generation time).

Supplementary File 4. Differential expression of RNAs control *versus M.tb*

infected AMs in all 28 donor AMs at 2h, 24h and 72h (Suppl. Files 4A, B, and C),

using separate non-infected control AMs for each time point. baseMean: log2

RPMs in control cells at each time point; log2FoldChange: RPM ratios of

infected/control. lfcSE: log fold-change standard error, stat: test statistic from DESeq2;

pvalue: unadjusted p values. padj: FDR-adjusted p value.

Supplementary File 5: A. Variably expressed genes (VE genes). RNAs displaying

the most variable expression between AMs based on variance and entropy in AM

controls and *M.tb*-treated cells. All of the most variably expressed genes (VE Genes)

were also significant DE genes (VE/DE genes), hence ordered in decreasing DE Expr

Log2 Ratios (column C). All samples at all-time points were subjected to Levene's test

(using ratios of variances as a test statistic) (Levene, 1960) to find RNAs that are

differentially variable between control samples and *M.tb* stimulated AMs, yielding RNAs

with highest variance in cases that are induced (or inhibited) by *M.tb* stimulation only in

a subset of individuals (encoded by VE genes). A second analysis asked whether the

entropy of RNA expression in the *M.tb*-treated group is higher than expected given the

total entropy over all AM samples (Handelman et al. 2015), using a permutation test to

yield p-values for significance of the entropy computations. tau ratios are ratios of

standard deviations (non-treated/treated). FDR Levene and FDR entropy are the

respective adjusted p values. Columns I, J, and K present correlation values (r, red

positive, blue negative) for each VE/DE gene with generation time over 48-72h (as in

Suppl. File 3), using RPM expression values for each gene at 2, 24, and 72h in infected

AMs. **B. Reactome Pathways significantly overrepresented among VE genes.**

Results are from reactome.org/PathwayBrowser using 324 VE/DE genes.

Supplementary File 6: A. Network module gene membership and correlations

between RNA expression (log2 RPMs) at 2, 24 and 72h in infected cells, and *M.tb*

generation times (*aka* RLU ratios, growth rates, 48-72h) in *M.tb* infected and control

AMs. **B. Genes with a significant association between growth rate and expression**

after FDR correction within modules. Correlations are as indicated in Supplementary

Files 3 and 5. The yellow module itself (24h RPMs) is also significantly correlated with

generation time.

Supplementary File 7. Summary of significant correlations between protein levels

and gene modules in control and infected AMs at 2, 24 and 72 h. Significant module

correlations with generation time are also indicated (blue, red, tan, yellow; 'yes'; column

D). CCL3 is present in multiple modules. Negative correlations are highlighted in red**.**

Adjusted p values reflect the number of proteins (n=27) and number of modules.

Supplementary File 8. GO term enrichment for 72hr gene modules. These four

modules (blue, yellow, tan red) are significantly correlated with *M.tb* generation times

(see Suppl. File 6). Results are from http://www.webgestalt.org/.

Supplementary File 9: A-F. Correlations between protein levels and gene

modules in control and infected AMs at 2, 24 and 72 h. Shown are correlations (r,

upper panels) and Adjusted p values (lower panels). Significant correlations are

highlighted. A few strong correlations occur in the uninfected cells (for example at 2h:

CCL3 with the Royalblue module (r=0.80, p=7.9e-7), CXCL5 with the Purple module

(r=0.72, p=3.7e-5), and IL6 with the Royalblue module (r=0.70, p=6.6e-6). Positive

correlations are highlighted in red, negative in blue (most in the infected AM

correlations)**.** Adjusted p values reflect the number of proteins (n=27).

Supplementary File 10. Differentially expressed genes selected from a curated

M1/M2 macrophage gene list (Table 1

in https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6618143/). Listed are DE in our

dataset at any single time point. The genes are labelled as relevant to M1 or M2 state,

the gene name, and the broad category (Transcription Factor, Surface Marker,

Released Cytokine or Metabolic Enzyme) and sub categories such as M2A/M2B/M2C

or OXPHOS/GLYCO. Fold change pval and Fold change data are from Supplementary

Files 4A-C.

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Figure 1 - figure supplement 1. **The transcriptional response of 28 human AM cultures to *in vitro* incubation and to *M.tb* infection.** A principle component analysis of normalized gene expression reveals the impact of cell culture conditions with and without *M.tb* infection.

Figure 7 – figure supplement 1. Top scoring network of DE genes with highly variable expression (VE/DE genes). The Ingenuity Pathway Analysis (IPA) (https://www.qiagenbioinformatics.com/products/ingenuity-pathway-analysis/) of VE/DE genes (n=324) generates a top scoring gene network, with IL1B on top. The same pathway is shown in Figure 7, while this graph displays all gene names.