Blood transcriptomics for TB diagnosis and monitoring treatment-response

Dr Jackie Cliff



How can blood transcriptomics help?

- Improved diagnostics for tuberculosis more rapid testing
- Measurement of drug treatment efficacy
 - Clinical trials of new drugs or regimens
 - Shortened treatment
 - Anti-microbial resistance
 - Latent TB treatment
 - Stratified medicine
- Stratification in vaccine trials











In order to develop biomarkers for clinical use, we need to use an accessible sample





Kaufmann *et al, The Lancet* 2010 375, 2110-2119



First question: can we detect different stages of infection using blood transcriptomics?





Active Recurrent Cured Latent Normalized expression

n = 10 per group

An algorithm based on expression of only 9 genes could discriminate the groups





LONDON

MEDICIN

HYGIENI &tropica

Similar results have been found by other researchers



OPEN access Freely available online			
Genome-Wide Express	ion Profiling Identifies Type 1		
Inte J Mol Med (2007) 85:613–621 DOI 10.1007/s00109-007-0157-6			
Tom H. Edhyan ORIGINAL ARTICLE			
Sangko 1 Infectious Netherlands	Vol 466 19 August 2010 doi:10.1038/nature09247	nature	
and disease cause		LETTERS	
Marc Jacobsen • Dirk Repsilber Albert Neher • Knut Feldmann Andreas Ziegler • Stefan H. E.	An interferon-inducible neutrophil-driven blood transcriptional signature in human tuberculosis		
	Matthew P. R. Berry ¹ , Christine M. Graham ¹ *, Finlay W. McNab ¹ *, Zhaohui Xu ⁶ , Susannah A. A. Bloch ³ , Tolu Oni ^{4,5} , Katalin A. Wilkinson ^{2,4} , Romain Banchereau ⁹ , Jason Skinner ⁶ , Robert J. Wilkinson ^{2,4,5} , Charles Quinn ⁶ , Derek Blankenship ⁷ , Ranju Dhawan ⁸ , John J. Cush ⁶ , Asuncion Mejias ¹⁰ , Octavio Ramilo ¹⁰ , Onn M. Kon ³ , Virginia Pascual ⁶ , Jacques Banchereau ⁶ , Damien Chaussabel ⁶ & Anne O'Garra ¹		

The Interferon-inducible neutrophil driven signature





Identified a 393-gene signature, which discriminates Active TB from health

Can assign individuals to groups

Berry, O'Garra et al, Nature 2010

In Active TB, blood transcriptomes revert to health during treatment



27 active TB cases recruited at Stellenbosch University, Cape Town, successfully cured by conventional treatment



Average changes in gene expression over 6 months



Cliff et al, 2013, J Infect Dis

Gene expression changes early and late reflect different phases of treatment and disease resolution





Prediction of TB-relapse after apparently successful cure





Log₂ normalised hybridisation intensity



Cliff et al, 2016, J Infect Dis

Patients recruited at diagnosis of first episode of TB, then followed up to see who subsequently relapsed

Diluted whole blood, stimulated with *M. tuberculosis* for 6 days

10 Patients who remained Cured for 2 years follow-up

10 Patients who suffered TB-relapse within 2 years

668 genes consistently differentially expressed between relapse and cured patients in ANOVA

A reduced signature is more useful for





Prediction of relapse can be achieved with 668 genes in most individual patients

An 18 gene signature, based on the most stringently differentially expressed genes in ANOVA, has high predictive sensitivity and specificity

Largely due to excessive cytolytic response in Relapse patients





Studies are reproducible across settings and technology platforms





Modular analysis has shown that most datasets contain common signatures

But most studies only include uncomplicated pulmonary TB cases

Blankley, O'Garra et al 2016

Common pathways across tuberculosis patient groups





Blankley, O'Garra et al 2016

Landmark study which incorporated non-straight forward tuberculosis

OPEN CACCESS Freely available online SA / Malawi HIV+/-test cohort Validation dataset B. Α. Detection of Tuberculosis in HIV-Infected and -Uninfected African Adults Using Whole Blood RNA 40 **Expression Signatures: A Case-Control Study** Disease risk score Disease risk score 09 30 Myrsini Kaforou^{1,23}, Victoria J. Wright¹³, Tolu Oni^{1,33}, Neil French^{4,5,63}, Suzanne T. Anderson^{7,8}, +0 4 M _ 39675 • 4 M _ 41865 120 Nonzwakazi Bangani³, Claire M. Banwell^{7,8}, Andrew J. Brent^{1,9}, Amelia C. Crampin^{4,6}, Hazel M. Dockrell¹⁰, Brian Eley¹¹, Robert S. Heyderman^{8,12}, Martin L. Hibberd¹³, Florian Kern⁷, Paul R. Langford¹, Ling Ling¹³ 10 Marc Mendelson¹⁴, Tom H. Ottenhoff¹⁵, Femia Zgambo⁴, Robert J. Wilkinson^{1,3,161}, Lachlan J. Coin^{2,171}, 8 Michael Levin^{1¶}* 20 8 TB vs. LTBI ΤВ LTBI TB LTBI Case-control cohorts in South Africa and Malawi 584 patients with 1.0 culture-confirmed TB 0.8 0.8 other disease, TB considered (OD) or Sensitivity Sensitivity LTBI or 0.2 "Kaforou signatures" – 44-gene (TB vs LTBI) or 27-gene (TB vs OD) mpirical Data Empirical Data 0.0

0.0

0.2

0.4

1-Specificity

0.8

1.0

0.0

0.2

04

1-Specificity

0.8



Summary part I



Blood transcriptomes can distinguish TB from healthy controls and from people with other diseases, and give early indication of disease

These signatures can also be used to monitor TB treatment-response, and with stimulation, potentially to predict TB-relapse

People are developing diagnostic tools based on large or small signatures

To really be useful, transcriptomic signatures need to be tested and developed in complex conditions

TB-diabetes co-morbidity



People with type 2 diabetes have a 3-fold increased risk of developing active TB once infected

Recent evidence – more likely to become infected

More likely to suffer poor TB treatment outcomes, including death, relapse and treatment failure



Overlap of the TB and T2DM epidemics





The TANDEM Study





RNA-Seq analysis – cross-sectional study



"complex design"

	TB only	DM only	DM-TB	IH-TB	Healthy controls
South Africa	11	33	15	20	24
Indonesia	14	-	19	5	-
Romania	10	19	15	10	12
Peru	11	-	12	9	-
TOTAL	46	52	61	44	36

Clare Eckold Cisca Wijmenga, Vinod Kumar, University of Groningen Medical Centre All TB patients were microbiologically confirmed pulmonary TB patients

Exclusions: HIV+, other serious co-morbidity, corticosteroid treatment

Samples collected prior to TB treatment commenced

Age, gender, ethnicity not different

Ex vivo blood samples collected into PAXgene tubes

Analysed by RNA-Seq

Intermediate hyperglycaemia



Normal glycaemia:

- HbA1c < 5.7%
- Fasting Plasma Glucose < 100mg/dl</p>

Diabetes:

- HbA1c ≥ 6.5%
- FPG ≥ 126 mg/dl

"Intermediate Hyperglycaemia"

– In between

Hypothesis/Expectations



TB is associated with a pro-inflammatory condition, upregulation of myeloid inflammatory genes

T2DM is also associated with increased inflammation

Hypothesis – people with T2DM – TB would have an exacerbated pro-inflammatory phenotype, which may cause excessive pathology relative to bacterial clearance

South African cohort, relative to Healthy controls





Comparison of comparisons for South Africa





The genes differentially expressed in DM are different to those differentially expressed in TB

The TB signature is dominant and amplified in DM



Principal component analysis of South Africans at baseline



The patients with DM-TB or IH-TB group together, distinctly from patients with only TB

PC1: 34% variance



Modular analysis of expression variation in South Africans



10⁻⁴ Effect size:

Combined analysis of all field sites





Summary of modular analysis in four sites



Across all four populations, there was a decreased interferon signature in diabetesrelated TB

The inflammation-related modules were further enhanced

"TB signature" has become uncoupled

NI BI GI APKI4 CTP2 UNISN LINISN HVTdO LAULID NITH HVTdO LAULID NITH HVTO S S

Inside: IHTB; outside DMTB

"TB signatures" should be adapted to consider DM





The Kaforou TB signature performed well on the TANDEM samples from TB-only patients, for TB classification

But it did not perform so well on the DMTB patients

The type 1 interferon effect





Summary



To summarise, we can develop gene expression based algorithms to be used as diagnostic tools for TB and to measure TB treatment-response

But these need to take into account other factors and morbidities, such as

diabetes

HIV

```
other co-infection – e.g. helminths
```

Age?

greater genetic variability

Impact of medications

Can this methodology be employed for monitoring latent infection and treatment efficacy?

Acknowledgements



<u>LSHTM</u>

Hazel Dockrell Clare Eckold JiSook Lee Taane Clark

Stellenbosch University Gerhard Walzl Rohit Mistry Paul van helden Nulda Beyers Pauline Lukey Ken Duncan Katharina Ronacher Stephanus Malherbe <u>University Padjadjaran</u> Rovina Ruslami Bachti Alisjabhana

<u>University of Medicine and Pharmacy of</u> <u>Craiova</u> Mihai Ioana Anca Riza

<u>Universidad Peruana Cayetano Heredia</u> Cessar Ugarte-Gil Jorge Coronel





BILL& MELINDA GATES foundation <u>University Medical College Groningen</u> Cisca Wijmenga Vinod Kumar

Radboud University Medical Center Reinout van Crevel Ekta Lachmandas Mihai Netea

Max Plank Institute for Infection Biology January Weiner

