Metabolic Biomarker Profiling to Understand Rheumatic Heart Disease Pathogenesis

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Background

Rheumatic heart disease (RHD) is leading cause of mortality among inflammatory heart diseases and acquired cardiovascular diseases globally ¹.

RHD is a sequela of Group A Streptococcus infection and acute rheumatic fever (ARF) (Fig.1).





Fig. 1 Diagrammatic representation of RHD pathogenesis. Infection with GAS bacteria, ARF Valvulitis and carditis followed by valve lesions, cardiomyopathies and RHD related mortalities

RHD prevalence at 4.6-7.9/1000 in LMICs leading to 1,426 disability-adjusted life-years per 1000 individuals ¹.

Cardiac surgery is the only proven intervention but not readily available in resource-limited regions especially in sub-Saharan Africa².

Biomarkers to be used for early detection and diagnosis of latent RHD ³.



Fig. 2 Schematic outlook of untargeted metabolomics workflow

Fig. 3 (A) Cloud plot of detected features in RHD cases (up regulated) and healthy controls (down regulated), the diameter of bubble indicates fold change and intensity of bubble color indicates p-value; 1643 m/z features were detected with p- value < 0.01. (B) PCA Scores plot analysis of significantly different features detected between RHD cases and healthy controls.



Fig. 4 (A) Volcano plot of significantly dysregulated metabolic features FC > 2; t-test p value < 0.005. (*B*) PLS-DA VIP scores plot of most predictive and discriminative features. (*C*) Orthogonal Projections to Latent Structures Discriminant Analysis (OPLS-DA) S-plot indicating important features with high reliability and intensities.

Table. 1 List of annotated and identified metabolic features indicating the rate of change (d.value), variability among replicates (stdev), p value and adjusted p value (qValue), name of metabolite, adducts ions, HMDB identifier and general role of the metabolites.





Objectives

The study aimed at applying metabolomics techniques to profile plasma/serum metabolic dysregulation biomarkers in patients diagnosed with RHD

Materials and Methods

Sampling

- Cases (RHD patients)
- Healthy Controls (age, sex & race)

Inclusion criteria

- RHD patients diagnosed at GSH (WHF 2014 criteria)
- Patient's age; 18-65 years old

Exclusion criteria

- Infective endocarditis
- Other inflammatory diseases
- Patients unable to consent
- HIV positive patients
- With other known cardiac diseases

122.0959715.1930.0806538.38E-050.0026142,6-XylidineM+HLidocaine (local
anesthetic) action
pathwayHMDB0060677928.611485.82370.0288840.0003710.002614Lactosylceramide (d18:1/12:0)M+KCell proliferation,
adhesion, migration
and angiogenesis,
cardiovascular
diseasesHMDB00173

Fig 5. KEGG metabolic pathways enrichment plot of the significantly identified metabolic biomarkers. Pathway impact determined by number of detected metabolites mapping onto the pathway

Using statistical analysis, significant features were extracted (Fig. 3-4). The significant features were annotated for metabolite identification using HMDB library matching and the general role of metabolites evaluated (Table. 1). Seventy-nine significant metabolites were identified as potential biomarkers (p value<0.05). Phosphatidylglycerol, phosphatidylcholine and cortexolone were among the highly significant potential biomarkers (relative difference >30, p<0.001). Identified metabolites were mapped on to 8 super pathways using high quality KEGG metabolic pathways; sphingolipid, glycerophospholipid, linoleic, alpha-linoleic acid, arachidonic acid and glycerolipid metabolism (Fig.5).

Conclusions and recommendations

These preliminary results indicate application of metabolomics and bioinformatics in identification of potential biomarkers in RHD. The results suggest a strong association between lipid metabolism dysregulation and RHD pathophysiology. We recommend conducting further experiments with a bigger sample size.

Sample collection and processing (Metabolites extraction)

References

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