Affinity proteomics reveals elevated muscle proteins

in plasma of children with cerebral malaria

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Legends to Supplementary Information

Figure S1. Intra-assay and inter-assay variance of suspension bead array. A) To analyze the intra-assay variance of one multiplex array, the coefficient of variation (CV) of each antibody ($k=384$) was determined in sample replicates ($n=24$) of one array experiment. 350 antibodies showed a CV of $\leq 10\%$ and only 2 antibodies were $\geq 20\%$. B) The technical interassay variance was evaluated by comparing sample-wise and antibody-wise correlations of two independently performed array experiments. The Spearman correlation coefficient between each duplicated sample was *rho*<0.94. Antibodies in two independent arrays showed a median Spearman *rho*=0.88 ranging between 0.45 and 0.99. In both experiments two samples were excluded due to technical failure. C) Sample- and antibody-wise correlation coefficients for the 24 duplicated patient samples in discovery and verification set with the top 29 proteins.

Figure S2. A) Principal component analysis (PCA) visualizing samples of "random" and "targeted" antibody profiling $(k = 384 \text{ antibodies}, n = 354 \text{ samples})$. B) Principal component analysis (PCA) of samples with the top significant 29 proteins from the "targeted array" ($k =$ 29 antibodies, $n = 354$ samples). Three-dimensional plots based on the first three dimensions of the PCA results are presented. All samples are colored based on the respective group affiliation. C) Heatmap showing protein profiles of the identified 29 host proteins. Samples were clustered based on Euclidian distance using the complete linkage method for hierarchical clustering. Proteins were sorted according to SOTA clusters. $CC = grey$, $UM =$ green, $SMA = red$, $CM = blue$.

Figure S3. Correlations and boxplots of the 29 identified discriminatory proteins from the 'targeted array'. The discovery screening using the 'targeted array' was performed in two independent experiments. For each of the 29 significant proteins corresponding correlations with the Spearman coefficient (*rho)* and boxplots from experiment 1 (Exp1) and the replicated experiment 2 (Exp2) are represented. All antibodies with significant differences showed *rho*>0.8.

Figure S4. Boxplots of the identified proteins from the 'random arrays'. Aiming at the identification of new proteins that have not been described in the context of malaria before, a part of the discovery screening was performed using 'random arrays'. These were created using a random selection of 760 antibodies being compiled from the collection of validated antibodies within HPA. Applying a non-parametric test (Kruskal-Wallis), 12 proteins were identified showing significant differences (p<0.001) between at least two of the four groups. ADSSL1 = adenylosuccinate synthase-like 1, CEBPA = $CCAAT/enhancer$ binding protein $(C/EBP)/a$ lpha, FAM71F2 = family with sequence similarity 71/ member F2, MSRB1 = methionine sulfoxide reductase B1, HAP1 = huntingtin-associated protein 1, DAPK1 = deathassociated protein kinase 1, DNPEP = aspartyl aminopeptidase, MYO15A = myosin XVA, CCDC102A = coiled-coil domain containing 102A, $SEC24C = SEC24$ family, $EEF2 =$ eukaryotic translation elongation factor 2, TIPIN = TIMELESS interacting protein.

Figure S5. Single proteins with significant differences between the three malaria disease groups. For pairwise comparisons of the groups, Wilcoxon rank sum test was applied (with continuity correction). A volcano plot displaying the relationship between the fold-change and significance was generated. Proteins with a p-value $\leq 0.1^{-6}$ (corresponds to Bonferroni adjusted p-value < 0.001) are displayed in red. See Table S1 in Text S1 for further details.

Figure S6. Technical verification of multivariate model and variable selection refinement. A) Area under ROC curve (AUC) of identified combinatory panels using the technical replicate data set in the discovery phase. For a first verification of the identified multi-protein signatures, the parameter estimates from the first dataset were used to obtain the prediction based on the second replicate data of the discovery cohort. B) Variable selection refinement. In order to investigate, which proteins contribute predominantly to the classification performance, the classifiers were sorted based on their absolute parameters obtained from L1-penalized logistic model. The logistic models of top *k* proteins were fitted and the AUC was calculated for each model. The effect on the classification performance of including the proteins is represented by the improvement of the AUC (see also Table S2 in Text S2).

Figure S7. Boxplots of CA3, CK and VWF analyzed with different antibodies in the discovery and the verification set. Various antibodies generated against different antigen sequences were used to validate the protein profile of (A) CA3, (B) CK and (C) VWF in the discovery and in the verification cohort. CA3: Carbonic anhydrase (R&D, #AF2185), CKM: Creatine kinase-M isoform (R&D, #MAB5564 and #G113C), vWF: von Willebrand Factor. $DC = Discovery$ cohort, $VC = Verification$ cohort.

Figure S8. Immunohistochemical analysis of antibodies using bright field microscopy. A) Protein expression (brown) and counterstaining (blue) of anti-CA3, -CK and -MB antibodies on healthy adult tissues is presented. All 5 antibodies showed cytoplasmic positivity in skeletal muscle. Heart muscle displayed cytoplasmic immunoreactivity with 3 out of 5 antibodies used in the study. One candidate showed negative cytoplasmic staining in CNS. B) Immunohistochemical analysis of anti-VWF and anti-SERPINA3 antibodies. Most tissues showed moderate to strong immunoreactivity in blood vessels. HPA00893 lacked blood vessel positivity in heart muscle. HPA02560 showed weak positivity in heart muscle and lacked immunoreactivity in cerebellum. CK: creatine kinase; CA3: Carbonic anhydrase 3; MB: Myoglobin; VWF: von Willebrand Factor; SERPINA3: serpin peptidase inhibitor, member 3.

Figure S9. Properties of targeted antibody array. Ingenuity Pathway analysis software (Igenuity Systems) was used to identify the most important canonical pathways that were enriched in the selected antibody array compared to the Ingenuity default background. *Acute phase signaling* was enriched most significantly and is displayed. Nearly all plasma proteins that are secreted during *acute phase signaling* were covered in the targeted array (orange circles). In the SOTA cluster 'Malaria increased' (see Fig. 2) were found 6 of 46 acute phase signaling plasma proteins: CRP, LBP, ORM1, SERPINA3, TNFRSF1B and VWF (red circles).

Figure S10: Boxplots of the significant proteins and muscle proteins from the DC cohort. The verification screening using was performed in an additional group to the discovery cohort and directely compared to the CM group. The Boxplots for muscle specific proteins and significant proteins is shown .

Table S1. Univariate two-group comparisons.

Table S2. Plasma protein signatures discriminating malaria disease groups after variable selection refinement.

Table S3. Antibody-antigen properties**.**

Table S4. List of target proteins used in the targeted array

Methods S1. More detailed information regarding the procedures utilized for: Case definitions, Clinical data and sample collection, Biotinylation of plasma samples, Quality assessment of suspension bead-array, Immunohistochemistry, Self-organizing tree algorithm (SOTA) analysis, Multivariate analysis.

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Figure S1.

Figure S2.

Figure S3.

Figure S4.

Figure S5.

Figure S6.

Figure S7.

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Figure S8.

Figure S9.

Figure S10.

Supplementary Tables

Table S1.

5 * was excluded from verification cohort

Table S2.

Table S3. Antibody-antigen properties.

Table S4.

Methods S1

Clinical data and sample collection. A 2.5 ml blood sample was obtained from each participant in an EDTA blood collection tube for subsequent plasma separation. Blood samples were kept on ice and transferred to the central malaria laboratory. Plasma for this study was harvested by centrifugation (1000 *g*, 10 minutes), aliquoted and frozen at -80°C no later than 4 hours following collection. The total of freeze/thaw cycles was limited and did not exceed 3 times during the entire study.

Biotinylation of plasma samples. Biotinylation was performed as previously described ¹ (refer to Supplementary Methods). Briefly, plasma samples were diluted using a liquid handler (SELMA, CyBio). Primary amino groups of plasma proteins were labeled using Nhydroxysuccinimide ester-biotin with a polyethylene oxide spacer (NHS-PEO4-Biotin, Pierce) as biotinylation reagent following the manufacturer's instructions. After incubation for 2 h, the reaction was stopped by the addition of 1 M Tris–HCl, pH 8.0 and samples were stored at −20°C. Two samples of the discovery cohort and four samples of the verification cohort had to be removed due to technical failure.

Quality assessment of suspension bead-array. To analyze the technical variation of the array, the initial screening using the 'targeted array' including 356 samples and 384 antibodies was reproduced in an independent experiment. The median coefficient of variation (CV) of sample replicates (n=12) within one experiment (intra-assay) was 5.5% for normalized data (Fig. S1A). To evaluate the inter-assay variation, the relative intensities between the two independent experiments were compared (Fig. S1B). The sample-wise median correlation coefficient was 0.992 ranging from 0.94 to 0.99. To assess the reproducibility also antibody-wise, the relative intensities of each antibody were compared in the two experiments. The correlation coefficients of antibodies ranged from 0.45 to 0.99 with a median of 0.89. Patient- and antibody-wise correlation coefficients were additionally determined for the 24 duplicated patient samples in discovery and validation cohort with the top 30 proteins. The median correlation coefficient for antibody-wise correlations was 0.67 and for sample-wise correlations 0.64 due to the low number of samples (Fig. S1C).

In general, many substantial differences ($p \le 0.001$) in protein profiles were found between the patient groups when utilizing the 'targeted array'. In order to confirm that the observed differences were specific to the pre-selected set of proteins in the 'targeted array', profiling with 'random arrays' was conducted. To obtain an overview of the observed differences in the 'targeted array' and the 'random arrays' principal component analysis (PCA) was performed, which provides a visualization tool for information-rich data by reducing the dimensionality. By projecting the data into the first few principal components, separations between disease groups can be observed dependent on the variables (proteins). Interestingly, the PCA of the 'targeted array' indicated a more spread separation by the proteins contained in this array compared to the 'random array' (Fig. S2A). Hence, the observed large differences were specific to the selected antibodies.

Immunohistochemistry. Immunohistochemical analysis was performed on healthy adult Human tissues as described before according to the Human Protein Atlas (HPA) standard operating procedures 2 . All incubations were performed at room temperature and reagents were from Thermo Fisher Scientific, unless specified. Briefly, prior to immunostaining, deparaffinization and hydration in xylene and graded ethanol to distilled water using a Leica Autostainer XL (Leica Biosystems, Wetzlar, Germany) were performed. Endogeneous peroxidase was blocked using $0.3 \% H_2O_2$ in 95% ethanol for 5 minutes. Pressure boiling (Decloaking chamber, Biocare Medical, Walnut Creek, CA) with retrieval buffer pH6 for 4 minutes at 125°C was carried out to perform heat induced epitope retrieval (HIER). After HIER, slides were allowed to cool to 90°C. Immunohistochemistry was performed using an Autostainer 480 (Thermo Fisher Scientific, Waltham, MA, USA). Between procedures described below, sections were washed in wash buffer twice. To block cross reactivity, incubation with UV block for 5 minutes was performed. Rabbit polyclonal antibodies affinitypurified using the antigen as affinity-ligand 3 and secondary labeled horse radish peroxidasepolymer were incubated for 30 minutes, respectively. Thereafter 3,3´-Diaminobenzidine (DAB) was used for detection for 10 minutes. Counterstaining was performed using hematoxylin (Histolab, Järfälla, Sweden) for 5 minutes and then the slides were rinsed in tap water and lithium carbonate water, diluted 1:5 from saturated solution, in total 10 min. Finally, the slides were dehydrated in graded ethanol. Stained slides were scanned using an automated high-resolution slide scanner (Aperio Technologies, Vista, CA, USA).

Self-organizing tree algorithm (SOTA) analysis. The SOTA algorithm combines the advantages of both hierarchical clustering and Self-Organizing Maps (SOM). Briefly, it picks

a node with the largest diversity and splits it into two nodes⁴. The tree was allowed to grow for 4 cycles. To visualize the high dimensional array data set we applied principal components analysis (PCA) using the R function prcomp⁵⁻⁷. Thereby, the dimensionality of the data set was reduced while maintaining as much variance as possible. Calculation is done by a singular value decomposition of the scaled and centered data matrix.

Multivariate analysis. Several logistic regression models with different variables (sex, age proteins) were fitted. In order to achieve a robust result, in each model hundred fits with different random seeds were performed. Based on the resulting λ_1 -value in each fit, the average λ_1 was used to fit the model. Because the variables age and sex did not provide large contribution to the classification, the analysis was continued using only proteins as variable for classification. The resulting protein panels as well as the corresponding area under the ROC curve (AUC) of each model is presented.

L1-penalized logistic regression model

Multiclass classification and at the same time performing feature (e.g., proteins) selections commonly faced in many biological applications is not a trivial problem. One way to deal with multiclass (i.e., UM, SMA and CM) classification is to decompose the classification into several binary classification tasks (one-vs.-one). Then, on each binary classification, binary classifiers are obtained using a binary classification method, i.e., L_1 penalized-logistic regression.

Logistic regression is a supervised method for binary classification 8 . Because it is a simple, flexible and straightforward model that is easy to extend, the extensions of logistic regression have been widely used in genomics and proteomics research ^{9, 10}.

In high-dimensional datasets such as an array, where usually variables are in similar or higher numbers than observations are available, and where the variables are correlated (multicollinearity), the classical logistic regression would perform badly and provide inaccurate estimates. It could result in a perfect fit to the data with no bias and high variance, which would lead to inaccurate predictions. In order to prevent this problem, a penalty for complexity in the model was introduced.

In our case, *yi* is an array of two malaria disease subtypes (i.e., cerebral malaria (CM), severe malarial anemia (SMA), or uncomplicated malaria (UM)), and *xj* is the intensity level of the *j*th protein. We can fit the following logistic model:

$$
\log it(\boldsymbol{p}(\mathbf{x}_i)) = \beta_0 + \sum_{j=1}^{m} \beta_j \mathbf{x}_j
$$

where $p(x)$ is the probability of success (i.e., $y = 1$) given x. To fit this model, the following log-likelihood had to be optimized:

$$
\ell(\beta) = \sum_{j=1}^n \{y_j \log(\rho(\mathbf{x}_j)) + (1 - y_j) \log(1 - \rho(\mathbf{x}_j))\}
$$

To penalize logistic regression, we can impose a penalty as defined in the following penalized log-likelihood:

$$
\ell^*(\beta) = \ell(\beta) - \lambda \mathsf{J}(\theta)
$$

where $J(\theta)$ is a penalty function. There are several penalty functions being proposed, and in this study we implement the ℓ_1 penalization proposed by Tibshirani¹¹ and known as Lasso. The ℓ 1 penalization use

$$
J(\theta) = \sum_{i=1}^{n} ||\theta_i||
$$

as the penalty function. The Lasso shrinks all regression coefficients *β* toward zero and set some of them to zero. Hence, it performs parameter estimation and variable selection at the same time. For a defined value of λ , the challenge is to optimize the penalized log-likelihood. Goeman 12 proposed the *full gradient* algorithm for maximizing Lasso-penalized loglikelihood. The choice of the tuning parameter λ is crucial. Since the *full gradient* algorithm finds the estimates of regression coefficients for a fixed value of λ , the optimal value of λ is found by a cross-validation procedure. In this procedure, cross-validated partial log-likelihood for a range of λ was calculated and the λ value, which gives the maximum log-likelihood is selected using Brent's algorithm ¹³. These algorithm and procedures are implemented in an R package called penalized 12.

Note that the sample partitioning in the cross-validation procedure are performed randomly, which can lead to slightly different λ values for different random seed numbers. To obtain the more reliable λ , 100 cross-validations are performed with different random seed numbers and the obtained (λ 1, λ 2, ..., λ 100) are averaged ($\overline{\lambda}$). The final ℓ 1-penalized model is then fitted based on the $\bar{\lambda}$.

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