A prioritized and validated resource of mitochondrial proteins in *Plasmodium* identifies leads to unique biology

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Abstract

Plasmodium species have a single mitochondrion that is essential for their survival and has been successfully targeted by anti-malarial drugs. Most mitochondrial proteins are imported into this organelle and our picture of the *Plasmodium* mitochondrial proteome remains incomplete. Many data sources contain information about mitochondrial localization, including proteome and gene expression profiles, orthology to mitochondrial proteins from other species, co-evolutionary relationships, and amino acid sequences, each with different coverage and reliability. To obtain a comprehensive, prioritized list of *Plasmodium falciparum* mitochondrial proteins, we rigorously analyzed and integrated eight datasets using Bayesian statistics into a predictive score per protein for mitochondrial localization. At a corrected false discovery rate of 25%, we identified 445 proteins with a sensitivity of 87% and a specificity of 97%. They include proteins that have not been identified as mitochondrial in other eukaryotes but have characterized homologs in bacteria that are involved in metabolism or translation. Mitochondrial localization of seven *Plasmodium berghei* orthologs was confirmed by epitope labeling and co-localization with a mitochondrial marker protein. One of these belongs to a newly identified apicomplexan mitochondrial protein family that in *P. falciparum* has four members. With the experimentally validated mitochondrial proteins and the complete ranked *P. falciparum* proteome, which we have named PlasmoMitoCarta, we present a resource to study unique proteins of *Plasmodium* mitochondria.

Introduction

Although all mitochondria evolved from a single endosymbiotic event (1), they display a large variety among the eukaryotes. For example, while in most species the mitochondrial organelle still retains its genome, the number of proteins encoded varies from 100 in *Andalucia godoyi* (2) to three in myzozoan species like *Plasmodium falciparum* that only encode cytochrome b, cytochrome c oxidase subunits 1 and 3, and two fragmented rRNAs (3). Moreover, mitochondria-like organelles of a variety of anaerobic species have lost the organellar genome altogether (4). Also mitochondrial proteomes vary broadly in size, ranging from e.g. ~1500 different proteins in mammalian mitochondria (5) to a few members of only a single biochemical pathway found in some mitosomes (6). Within this variety, the *P. falciparum* mitochondrion, based on the size of its genome, the size of the nuclear genome, and the complexity of its oxidative phosphorylation, is predicted to have a relatively small proteome. Although several mitochondrial pathways have already been identified in *P. falciparum* (7), and databases like PlasmoDB contain valuable information about mitochondrial localization of individual proteins (8), a complete resource that weighs and combines all the relevant information about possible mitochondrial localization is lacking.

Plasmodium mitochondria are particularly interesting because their function is variable between different life-cycle stages. In the sexual blood stage, functional oxidative phosphorylation is essential for colonization and development inside the mosquito hosts (9, 10), while in asexual blood stages the only essential function of the respiratory chain is to recycle ubiquinone for pyrimidine biosynthesis (11). This is further highlighted by the observation that in asexual blood-stage parasites no cristae are detectable in the mitochondrial membrane, while in gametocyte mitochondria cristae-like structures that typically accumulate respiratory chain complexes are observed (10, 12). A recent complexome profiling study demonstrated that the level of complex V components in asexual blood-stage parasites was only 3% of the level in gametocytes (12). Another intriguing aspect of mitochondria in *Plasmodium* and closely related species is that they have a rather unique FeS cluster assembly pathway (13). From this pathway the frataxin protein, an FeS assembly protein that occurs even in mitosomes (14) appears to be missing in *Plasmodium* (15).

Knowledge on the mitochondrial proteome could provide viable targets for the development of new drugs against this deadly parasite, as apicomplexan mitochondrial

proteomes contain unique proteins that are not present in the animal hosts (16). Recently for

example, an unusual prohibitin-like protein, PHBL, was identified in *Plasmodium berghei* that

might provide a transmission-blocking drug target as it is unique to Myzozoa and *phbl*⁻

parasites fail to transmit (17). Furthermore, respiratory protein complex III has proven to be

a good drug target (18) and inhibitors to the mitochondrial enzymes dihydroorotate

dehydrogenase (DHODH) and NADH type II oxidoreductase (PfNDH2) have been identified

(19).

For years, it has been difficult to perform proteomics experiments to identify the

Plasmodium mitochondrial proteome due to the lack of organelle isolation methods that

reliably separate mitochondria from the apicoplast (20). The definition of mitochondrial

functions relied heavily upon homology studies (7, 21) and microscopic examination of

individual proteins (Supplemental Table 1). With the use of two biotin tagging approaches,

422 mitochondrial matrix proteins were identified in *Toxoplasma gondii*, a species related to

Plasmodium that also has an apicoplast and a mitochondrion (16). Besides these

mitochondria-targeted approaches, hyperLOPIT, a whole-cell biochemical fractionation

technique, defined the subcellular localization of the *T. gondii* proteome. This provided

among others a set of 220 soluble and 168 membrane-bound *T. gondii* mitochondrial proteins

(22). Alongside these proteomic data, there is a wealth of other data sources providing

information on mitochondrial localization in *P. falciparum*. The challenge remains to use and

combine these heterogeneous datasets to reliably predict the mitochondrial proteome.

Here, we integrated eight datasets containing proteomic, gene expression, orthology

to mitochondrial proteins from other species, phylogenetic distribution, and amino acid

sequence data in a Bayesian manner as has been applied before such as for the definition of

the mitochondrial proteome of humans (13) and of developmental stage specific proteins in

Plasmodium(23, 24). We used a naïve Bayesian classifier to combine the data. This method

exploits the relative strengths of the various datasets while maintaining transparency about

the contribution of each dataset to the final Bayesian posterior probability score for being

mitochondrial. For each protein, the contribution of each dataset to the prediction was

determined using gold standards of *Plasmodium* proteins that are either known to be

mitochondrial or non-mitochondrial. After data integration, we obtained a list of 445 P.

falciparum mitochondrial proteins. We experimentally validated these predictions with seven

proteins of varying probability scores, and collectively this predicted proteome indicates that

the *P. falciparum* mitochondria are unique relative to mitochondria of model organisms.

Materials and Methods

Animal experiments. All animal experiments were performed in accordance with the Dutch

Experiments on Animals Act (Wod), the Directive 2010/63/EU from the European Union and

the European ETS 123 convention and approved by the Radboud University Animal Welfare

Body (IvD) and Animal Experiment Committee (RUDEC; 2015-0142), and the Central Authority

for Scientific Procedures on Animals (CCD; AVD103002016424). In this study, we used

outbred male and female NMRI mice (Envigo).

Nuclear encoded reference proteome. All datasets used in this study were mapped to the

P. falciparum 3D7 reference proteome version 3.1 from the Sanger Institute, downloaded

December 2017. This version, including isoforms, contains 5431 proteins encoded by 5357

genes. As we are interested in the proteins encoded by nuclear genes, all apicoplast and

mitochondrial encoded proteins were excluded, leaving a reference of 5324 genes. When a

dataset contains informational data points for two or more protein isoforms of one gene, the

value chosen for that gene was the one that comes closest to the expected values for

mitochondrial proteins in that specific dataset.

Assembly of positive and negative lists for benchmarking. Bayesian data integration depends

on gold standards of proteins known to be mitochondrial or non-mitochondrial. We

constructed two gold standards to assess the predictive value of the individual datasets.

Furthermore, we built two alternative sets for the construction of the CLIME (co-evolution)

and WICCA (co-expression) datasets to prevent that the standards chosen to train those two

predictors were also used to evaluate them. Thus we avoid circular arguments in the data

integration. These four sets are unique, have no overlapping genes, and are available in

Supplemental Table 1. To construct these lists, we commenced with a systematic review of

all literature available via PubMed (as per 30-08-2018) using the following broad search string

"(mitochondri* OR apicoplast OR plastid) AND (plasmodium OR malaria)". Given the intimate

functional and physical relation between mitochondrion and apicoplast, we reasoned that

the positive gold standard list should only include genes encoding proteins that had been
unambiguously and singularly assigned to the mitochondrion through fluorescence
microscopy and co-localization with confirmed mitochondrial markers or via immune-
electron microscopy (54 genes). Any proteins for which multiple studies showed different
results were excluded. To facilitate discrimination from the apicoplast, we also made a gold
standard apicoplast list (72 genes). Finally, all proteins that were unambiguously non-
mitochondrial as demonstrated in the same papers (170 genes) were combined with the
apicoplast-positive list to form the basis for the negative gold standard. This negative set was
then complemented with an additional 346 non-overlapping genes encoding non-apicoplast
and non-mitochondrial proteins identified through extensive literature review and published
online by the Ralph lab (25). The 588 genes encoding non-mitochondrial proteins were
randomly assigned to the negative gold standard (294 genes) that was used for the Bayesian
data integration and the alternative negative gold standard (294 genes) that was used to train
the CLIME and WICCA approaches. For the latter purpose, an alternative positive standard
was compiled of 146 genes, non-overlapping with the first gold standard, but associated with
one or more mitochondrial GO-terms (GO:0000275, GO:0005739-43, GO:0005746,
GO:0005750, GO:0005753, GO:0005758, GO:0005759, GO:0006122, GO:0006839,
GO:0006850, GO:0031966, GO:0033108, GO:0042775, GO:0044429, GO:0044455).

Datasets to predict mitochondrial and non-mitochondrial proteins. To predict mitochondrial
proteins and non-mitochondrial proteins, we collected and constructed eight datasets (Table
1) that contain features typical of either mitochondrial or apicoplast proteins. Some proteins,
like lipoate protein ligase 2 (PF3D7_0923600) (26) and serine hydroxymethyltransferase
isoforms (PF3D7_1235600) (27), are dual localized to the mitochondrion and apicoplast,
highlighting the need for the second category of datasets. Each dataset is described in detail
below, including how the dataset was processed to obtain per *P. falciparum* protein a single
score relevant to whether the protein is mitochondrial or not.

Table 1: Input datasets for Bayesian integration.

Dataset	Abbreviations used in figures	Size of dataset	Fraction identified (%)	Fraction gold identified (%)	P - value
Dataset based on 'omics data					
Co-expression, built using in-house developed WICCA tool (rank ≤ 2400) (https://wicca.cmbi.umcn.nl/)	Co-expression	5310	45.6	83.0	2.0E-08
Non- Apicoplast proteins (28)	BioID, gene expression	5324	93.6	94.4	5.4E-01
Datasets based on ortholog evidence					
hyperLOPIT (TAGM.MCMC.joint.mitochondrion_max ≥ 4.78E-05) (22)	hyperLOPIT	2246	15	95.2	9.3E-32
Mitochondrial ortholog	Mito ortholog	5280	8.7	75.5	2.6E-32
Evolutionary inference, built using CLIME (NN score ≤ -1.5) (29)	CLIME	4687	9.0	38.5	6.9E-09
Absence of a *Cryptosporidium* ortholog (score ≤ 4)	Crypto ortholog	5280	67.5	77.4	7.9E-02
Datasets based on amino acid sequence evidence					
Mitochondrial targeting signal, built using PFMpred tool (SVM ≥ -0.67) (30)	Mitochondrial TS	5324	59.5	83.3	1.4E-04
Isoelectric point (Patrickios pI ≥ 4.2)*(28)*	pI	5324	55.1	83.3	1.1E-05

The size of datasets indicates the number of *Plasmodium* genes that could potentially have been measured in this dataset. Fractions indicate the actually identified genes of this set that fall in bins with a positive mitochondrial score (Fig 1A). P values (Fisher's exact test) indicate

176 overrepresentation of identified gold standard genes compared to random
177 expectation.Notice that in the "non-Apicoplast proteins" and in the "Absence of a
178 Cryptosporidium ortholog" these P values reflect the over representation of mitochondrial
179 proteins among the large sets of proteins to which these features apply.

Dataset based on 'omics data

Co-expression. Co-expressed genes tend to code for proteins that functionally interact. For mammals, co-expression analyses have been successfully used in the discovery of mitochondrial proteins (5, 31). To determine if the expression pattern of a *Plasmodium* gene correlates with mitochondrial protein coding genes, we developed a co-expression tool: WeIghted Co-expression Calculation tool for plAsmodium genes (WICCA, available at https://wicca.cmbi.umcn.nl/). In short, the tool uses the co-expression of a group of input genes with each other to weigh 83 microarray experiments for their predictive value for that group. Datasets that show high co-expression of the input genes are more likely to be relevant for the system that the input genes are part of, and receive a higher weight. It then uses these weights to combine the expression datasets and calculate one co-expression score per gene with the input system, in this case, one score per gene for the level of co-expression with mitochondrial protein coding genes. We used the co-expression ranking obtained with the alternative positive standard of 146 genes as input for WICCA to weigh the co-expression datasets. The methods of this tool were based on the WeGET method (http://weget.cmbi.umcn.nl/, (32)), methodological details on WICCA can be found in the supplement.

Bio-ID. In Bayesian data integration, "negative data sets" that e.g. predict that a protein is non-mitochondrial can be as valuable as positive ones**.** We used the set of 346 apicoplast proteins that are based on BioID data and gene expression data analyzed with a Neural Network (28) to reduce apicoplast protein contamination among the top scoring proteins.

Datasets based on ortholog evidence

hyperLOPIT. Hyperplexed Localization of Organelle Proteins by Isotope Tagging (hyperLOPIT) is a proteomics technique that analyzes protein distributions upon biochemical fractionation. It enables the identification of the subcellular localization of thousands of proteins (33, 34).

Barylyuk *et al.* used this technique on the apicomplexan *T. gondii* and, among others,
classified proteins identified in all three hyperLOPIT experiments to be part of the
mitochondrial soluble matrix and mitochondrial membrane. This classification was based on
t-augmented Gaussian mixture models (TAGM) in combination with maximum a posteriori
prediction (TAGM-MAP) and Markov-chain Monte-Carlo (TAGM-MCMC) methods (22).
Marker proteins used for the classification were arbitrarily set to 1 in the class that they
belong to and to 0 for all other classes. Using BLAST (35), or if that produced no homologs
HHpred (36), in combination with selecting for best bidirectional hits, we determined a list of
orthologs between *T. gondii* and *P. falciparum*. The 3,832 *T. gondii* proteins that got a TAGM-
MCMC probability for mitochondrial soluble matrix and mitochondrial membrane were
mapped to the corresponding *P. falciparum* ortholog when available. This resulted in a list of
2246 *P. falciparum* identifiers with two TAGM-MCMC probabilities, one for mitochondrial
matrix localization and one for mitochondrial membrane localization. As the input datasets
for the Bayesian integration should be independent, both TAGM-MCMC probabilities cannot
be included as separate datasets. Therefore the maximum TAGM-MCMC probability (so
either the soluble or the membrane value) for each protein was used to create one input
hyperLOPIT dataset.

Mitochondrial ortholog. We also used orthologs from more distantly related species
than *T. gondii*, as also at larger phylogenetic distances subcellular localizations tend to be
conserved (37). Using BLAST (35) (all versus all blast for proteomes with e-value of 100) in
combination with OrthoMCL (38) (percent match cut of 50, e-value exponent cut off -5) to
detect orthologs, or if that produced no result, HHpred (36) (default settings, e-value cut off
0.01, three iterations, only best-bi-directional hits included), one-to-one orthologs between
P. falciparum and either *Homo sapiens*, *Arabidopsis thaliana* or *Saccharomyces cerevisiae*
were determined. When the orthologous protein of at least one species was annotated to be
mitochondrial in a published mitochondrial compendium (*H. sapiens* MitoCarta2.0 (5), *A.*
thaliana (39), *S. cerevisiae* (40)), then that *P. falciparum* protein was included in the
mitochondrial ortholog dataset.

Evolutionary inference. Clustered by inferred models of evolution (CLIME) uses
homology across model species (138 eukaryotic species and 1 prokaryotic outgroup) to
identify evolutionary conserved clusters. We downloaded the pre-computed CLIME analyses
of *P. falciparum* genes from http://gene-clime.org/ (29) and mapped the IDs to our reference

proteome. We used the CLIME matrix listing the presence/absence of orthologs of
P. falciparum in other species, with the alternative positive and negative sets as training data,
to train a perceptron with two hidden layers to obtain a single score per protein (details in
supplement). The resulting output scores on our test set formed the CLIME input for the
Bayesian integration.

Absence of a *Cryptosporidium* ortholog. Like *Plasmodium*, the genus *Cryptosporidium*
belongs to the phylum of Apicomplexa. *Cryptosporidium* species lack an apicoplast and
contain only a remnant mitochondrial-like organelle (41). Therefore, it can be expected that
apicoplast proteins and many mitochondrial proteins will not have an ortholog in
Cryptosporidium. MetaPhOrs is an online tool that contains orthology and paralogy
predictions obtained from multiple phylogenetic trees (42) and was used to assess orthology
for *P. falciparum* genes in three *Cryptosporidium* species (*hominis, parvum*, and *muris*). We
calculated a combined score by multiplying two MetaPhOrs metrics, one for the confidence
level (see below) and one for the number of hits between the four species, and used this
combined score as input for the Bayesian integration. In detail, the MetaPhOrs results include
a consistency score (ranging from 0 with no overlap to 1 if all trees contain the same protein
relationship/orthology information) and an evidence level for the number of independent
databases (the theoretical maximum is 13, but for our species combination it was four). The
multiplication of consistency and evidence level results in an arbitrary score (range 0-4) that
indicates the confidence in calling two proteins orthologs. *P. falciparum* proteins with a high
score are more likely to have an ortholog in *Cryptosporidium*. Notice that there is some
overlap with the Evolutionary inference as that includes one *Cryptosporidium* species.
Nevertheless, *Cryptosporidium* species show quite some variation in the complexity of their
mitosomes and the overlap in the predictions is limited (see below).

Datasets based on amino acid sequence evidence
Mitochondrial targeting signal. The canonical mitochondrial import system requires an
amphipathic α-helical N-terminal targeting sequence. As *Plasmodium* has a distinct amino
acid usage pattern (43), a *P. falciparum* specific tool, PFMpred (30), was chosen to predict
mitochondrial localization based on the amino acid sequence. This is a support vector
machine (SVM) based tool and was used in split-amino-acid-composition mode (Matthews
correlation coefficient 0.73) that allows separate calculations for the N-terminus, C-terminus,

and remainder of the protein. The tool reports one SVM-score per protein and indicates

whether the protein is predicted to be mitochondrial or not. The SVM-scores per gene are

used as the mitochondrial targeting signal dataset.

Isoelectric point. Nuclear encoded mitochondrial proteins need to cross the

negatively charged mitochondrial membrane and need to function properly inside the

mitochondrial environment that has a slightly higher pH compared to the cytosol (44). A

density plot (Supplemental Fig 1) by Patrikios isoelectric points (45) of the human

mitochondrial proteome (MitoCarta2.0 (5)) showed that mitochondrial proteins on average

have a higher pI than the remainder of the proteome. Isoelectric points for the *P. falciparum*

proteome were calculated using the Patrickios algorithm (46) and directly used as pI scores.

Bayesian integration to predict mitochondrial proteins. Using the eight datasets described

above and the gold standard evaluation sets, a mitochondrial score for each *P. falciparum*

reference protein was calculated. This score is the logarithm of the odds that a protein is

localized in the mitochondrion relative to the protein being localized somewhere else in the

cell. For categorical data (mitochondrial ortholog, apicoplast targeting signal), the dataset is

separated into bins that represent the two categories. Continuous data (the other six

datasets) were binned in a systematic way using a custom python script

(https://github.com/JordyCoolen/Binning) (settings: --bins 0 --score 1). In short, this script

optimizes for each dataset the distribution of the bins such that the sum of log ratio scores of

all bins combined (see below) is close to zero, as this will result in the best separation of

positive and negative bins. The number of bins was varied to a maximum of five bins to

achieve the most optimal separation without expanding the number such that there are too

few proteins per bin to obtain reliable estimates of the log odds of that bin.

The fractions of gold standard proteins per bin are determined. The log ratio of these

fractions determines the score for all other proteins in that respective bin. The mitochondrial

score is based on the sum of log ratios of the individual datasets and is calculated as follows:

$mitochondrial\ score$

301
$$= log_2 \left(\frac{P_{mitochondrial}}{P_{non-mitochondrial}} \right) + \sum_{i=1}^{n} log_2 \left(\frac{P(data_i | mitochondrial)}{P(data_i | non-mitochondrial)} \right)$$

$$with \ \frac{P(data_i|mitochondrial)}{P(data_i|non-mitochondrial)} = \frac{mitochondrial\_pos_i}{mitochondrial\_neg_i}$$

where mitochondrial_pos and mitochondrial_neg are the fractions of the positive and

negative gold standard genes in sample i respectively. If there were no gold standard genes

found in a certain bin, that positive or negative gold standard fraction was set to 0.5/'total

number of negative set genes in the complete dataset' to prevent division by zero and allow

calculation of the log ratio. The O_{prior}, $\log_2(P_{mitochondrial}/P_{non-mitochondrial})$, is based on the

estimation that 536 proteins out of the 5357 protein coding genes (~10%) encode a

mitochondrial protein. This is a conservative estimate when compared to single cell species

like *Saccharomyces cerevisiae* with 16% mitochondrial proteins (47), or the more closely

related *T. gondii* where 15% of proteins that could confidently be mapped are mitochondrial

(48), while compared to all proteins that were mapped in that dataset the percentage of

mitochondrial proteins is 10%. Note that the O_{prior} only affects the score per protein, it does

not affect the relative ranking of potential mitochondrial proteins.

To assess the performance of the integration, a false discovery rate (FDR) was

calculated. As this FDR depends on gold standard genes and as the ratio gold

positives/negatives is not similar to the ratio of mitochondrial protein coding genes versus

non-mitochondrial coding genes in the genome, the FDR was corrected (cFDR) using the

following formula:

$$cFDR = \frac{1 - specificity}{1 - specificity + sensitivity \cdot O_{prior}}$$

Cross-validation. To assess the ability of the integrated predictor to discriminate known

mitochondrial proteins from non-mitochondrial proteins, ten-fold cross-validation was

performed. The gold standards (both negative and positive) were subsampled ten times,

thereby creating ten sets of nine-tenth of the gold standard genes. Each gold standard gene

was left out once in one of the ten sets. Data integration was performed with each of these

ten sets and the ranks of the one-tenth left out gold standard genes were retrieved. The ten-

fold cross-validated ROC curve was constructed based on those ranks.

Intraspecies homologs. The human mitochondrial proteome has expanded since the

divergence from yeast mainly due to gene duplications that create mitochondrial paralogs

(37). It is therefore interesting to see if the predicted *P. falciparum* mitochondrial proteins

have intraspecies homologs, and whether we can identify mitochondrial gene families. With

HHpred (36), using default settings and a 1E-5 E-value cut-off, the homologs within the

genome of *P. falciparum* were determined and included as a column in Supplemental Table

2.

Validation of candidate proteins. To validate the predictions, we selected 14 genes with

unusual or novel mitochondrial functions within the top 295 genes that fell within the 25%

cFDR cut-off in the initial data integration. Note that during the project, the number of

predicted mitochondrial proteins increased to 445 by including better orthology prediction

and a better data set of likely apicoplast proteins. Of these 14 genes, 13 were selected based

on maximum transcript levels during asexual blood-stage development of *P. berghei* strain

ANKA cl15cy1 that exceeded 100 FPKM (49). In addition, we selected one particularly

interesting gene, PF3D7_1004900 that had a lower transcript level. We used experimental

genetics (50) to generate *P. berghei* lines expressing 3xHA-tagged copies of the selected

proteins and colocalized them with an established mitochondrial marker (17) to determine

their subcellular localization by immunofluorescence microscopy. Details on plasmid

construction (successful for 13 out of 14 targets, excluding PF3D7_1142800) and the

generation of the lines can be found as supplemental information. To assess colocalization,

the freshly harvested transgenic parasites were allowed to settle on a poly-L-lysine coated

coverslip for 10 minutes and then fixed with 4% EM-grade paraformaldehyde (Fisher

Scientific) and 0.0075% EM-grade glutaraldehyde (Sigma-Aldrich) in microtubule stabilizing

buffer (MTSB, 10 mM MES, 150 mM NaCl, 5 mM EGTA, 5 mM glucose, 5 mM MgCl2 pH 6.9)

for 20 minutes (51). Next, parasites were permeabilized with 0.1% Triton X-100 in PBS for 10

minutes. Samples in which we imaged mOrange and mCherry were hereafter stained with

DAPI (1:300) for 15 minutes and mounted on a microscope slide with VectaShield (Vector

laboratories). All other samples were blocked in 3% FCS-PBS for 1 hour. Samples were

incubated overnight at 4°C with rat anti-HA (1:500, ROAHAHA Roche) and chicken anti-GFP

(1:1000, Thermo Fisher) antibodies and for 1 hour with 1:500 goat anti-rat Alexa fluor™ 594

(Invitrogen) and goat anti-chicken Alexa fluor™ 488 (Thermo Fisher) conjugated antibodies at

room temperature. Nuclei were stained with DAPI (1:300) for 15 minutes and coverslips were

mounted on a microscope slide with VectaShield (Vector laboratories). Samples were imaged

with an SP8 confocal microscope (Leica, 63x oil lens) or LSM900 confocal microscope (Zeiss,

63x oil lens). Images were processed minimally and similarly with Fiji (52).

Tools for data analysis. Plots, statistics, and calculations were performed with the R statistical

package (53) and additional packages gplots (54), ggplot2 (55), ROCR (56), scales (57) and

reshape (58). The separation of the datasets into bins was performed using a python script

(see above).

Results

We integrated eight features of proteomic, gene expression, orthology and amino acid

composition data, to predict mitochondrial localization in *P. falciparum*. All the individual

features had a predictive value for mitochondrial localization (Fig 1A and 1B), including, as

expected, a negative score for the "*Cryptosporidium* ortholog" and the "apicoplast" datasets

(Supplemental Fig 2A). Notice that for the co-expression feature it is the bin with the low-rank

values that contains most mitochondrial proteins because this bin contains the proteins with

the highest co-expression values. The best performing input datasets are the ones that

translate mitochondrial localization between species: the hyperLOPIT dataset and the

mitochondrial ortholog dataset, followed by the mitochondrial targeting signal and co-

expression datasets (Fig 1B). Correlation analyses showed that the features are largely

independent off each other, allowing us to use naïve Bayesian data integration (Supplemental

Fig 2B). The highest correlations were observed between features that examine the

phylogenetic distribution of the proteins: CLIME and *Cryptosporidium* ortholog datasets. By

integrating all data, we achieved both a better sensitivity and specificity in predicting

mitochondrial proteins with an AUC of 0.959 than we achieved for individual data sets (Fig

1B). The performance of the hyperLOPIT dataset on its own approximates the integrated

prediction with an AUC of 0.953 (Fig 1B). However, this dataset contains information on only

2246 (42%) of the nuclear encoded *Plasmodium* proteins, highlighting the value of additional

datasets and their integration to predict a complete mitochondrial proteome. The distribution

of the log-odds ratios (Fig 1C) showed that the mitochondrial score separated the positive

and negative gold standards well from each other and that there are additional proteins with

a high score that were not part of either, which are potential new mitochondrial proteins. We

use a cFDR of 25% (Fig 2A) as a threshold for highly probable new mitochondrial proteins and

identify 445 proteins (Fig 2B) with a sensitivity of 87% and a specificity of 97%. The ranked list

of the complete nuclear encoded proteome is available in Supplemental Table 2.

Comparison of the Toxoplasma and Plasmodium mitochondrial proteomes.

Overall, the hyperLOPIT dataset contains 388 *T. gondii* mitochondrial proteins with a TAGM-

MCMC location probability of 99% or higher. Of those, 296 have a *P. falciparum* ortholog and

of these orthologs, we find 273 in our predicted mitochondrial proteome. Most proteins that

we predicted to be mitochondrial that were not supported by the *T. gondii* data are proteins

that do have orthologs in *T. gondii*, for which there were however no hyperLOPIT data (95

proteins). There are furthermore 38 proteins in the set of 445 that do not have *T. gondii*

orthologs. It should be noted that these do not include the six *P. falciparum* mitochondrial

ribosomal proteins that, based on Blast searches, were deemed to be absent from *T. gondii*

(59), as for those we could identify orthologs using HHpred (Table S2), underlining the

relevance of sensitive homology detection. Finally, there are 39 proteins of which orthologs

are present in the hyperLOPIT dataset but fell outside the 99% cut off for mitochondrial

localization that was used in that study, 26 of these did still have a mitochondrial localization

as the most probable location and 13 had a different predicted location in *T. gondii* (flagged

in Supplemental Table 2). Manual examination of those 13 inconsistencies reveals proteins

like PF3D7_1125300/mitochondrial RNA polymerase that in the hyperLOPIT data has been

observed in the nucleolus, but also PF3D7_1446400/pdhB that was predicted to be

mitochondrial based on orthology with pdhB in e.g. *H.sapiens* but is localized in the apicoplast

in *Plasmodium(60)*.

Fig 1. Predictive values of the individual datasets and the integrated ranked list. (A) Barplot of each dataset with the fraction of the gold standards on the y-axis and the bins on the x-axis. In green, the mitochondrial score per bin is indicated to show the predictive value of each bin. (B) ROC-curves comparing the performance to identify mitochondrial proteins of the prediction (10-fold cross-validated) to the performance of the individual datasets. For

 comparison, the values for the area under each curve are indicated in the legend. (C) Boxplot

that visualizes the distribution of the gold-standard positives, negatives, and remainder of the

proteome (x-axis) over the calculated mitochondrial score of the prediction (y-axis).

Fig 2. Integration produces a ranked proteome with 445 likely mitochondrial proteins at a

25% cFDR-cut. (A) Density plot of the mitochondrial score with a colored bar at the bottom

indicating the scores of individual gold standards. The arrow indicates the 25% cFDR cut-off.

(B) The top 445 proteins falling in the 25% cFDR cut-off ranked on their mitochondrial score

with color indicating if the protein is part of a gold standard. Black arrows indicated the

ranking of the seven candidate proteins that we experimentally confirmed to be

mitochondrial (Fig 3A and 3B), dark grey arrows indicate the ranking of the three proteins

with suggested mitochondrial localization (Fig 3C), and light grey arrows the ranking of the

three proteins with inconclusive results (Supplemental Fig 4B). (C) Categorical representation

of the 445 proteins identified at the 25% cFDR cut-off. First, genes were separated into

categories based on the gold standard, the remainder on mitochondrial and apicoplast GO

term, and subsequently the remainder on gene function annotations.

Validation of candidates. We aimed to validate the mitochondrial candidate list by tagging

orthologs of the selected unusual or unique predicted mitochondrial proteins in the efficient

transfection model *P. berghei* (see the section 'new mitochondrial proteins' for the *P.*

falciparum orthologs of these proteins). Mitochondrial localization was assessed by

fluorescent microscopy using an experimental genetic approach developed in our lab (17).

This method allows the endogenous tagging of a target protein with a combined fluorescent

and epitope tag, while simultaneously introducing a strong mitochondrial targeted GFP

marker by fusion of the promoter and N terminus of HSP70-3 (PBANKA_0914400) to GFP.

Initially, we tagged 6 proteins with a mOrange-3xHA tag. Live imaging revealed very poor and

undefined signals (data not shown). Next, we fixed blood samples and stained them with anti-

HA antibodies. Using this approach, only PBANKA_0310100 and PBANKA_1203200 were

convincingly shown to localize to the mitochondrion (Fig 3A), while other proteins

demonstrated mostly undetectable or undefined signals (Supplemental Fig 4A). Since many

of the selected proteins are relatively small compared to the mOrange-tag and are expected

to be imported into the mitochondrion, we anticipated that interference of the tag with

import or proper folding could lead to the observed weak and undefined signals. To assess

this, we selected two similarly small and abundantly expressed targets, PBANKA_0310100

(127 amino acids) and PBANKA_1024800 (144 amino acids), to test different tags. For

PBANKA_0310100, which was already successfully localized to the mitochondrion, these

included tags consisting of only the fluorescent protein mOrange or only the 3xHA epitope

tag, either with or without a linker sequence. For PBANKA_1024800, we also included the

combined mCherry-cMyc tag that has previously been used successfully to tag mitochondrial

proteins (17). We found that the fluorescent protein tag indeed interfered with the

localization of PBANKA_1024800, while the 3xHA tag, with or without a linker, supported a

mitochondrial localization (Supplemental Fig 5B). Surprisingly, using the mOrange-tag

without the subsequent HA-tag also led to an undefined rather punctuate mislocalization of

PBANKA_0310100 (Supplemental Fig 5B). Based on these observations, we decided to tag the

remaining 11 proteins with a linker-3xHA-tag (Fig 3B, 3C and Supplemental Fig 4B). Five of

these were also convincingly localized to the mitochondria (Fig 3B), while an additional three

proteins showed very weak staining patterns suggestive of a possible mitochondrial

localization (Fig 3C). The signals of the remaining three tagged proteins were unable to be

distinguished from the background and therefore no subcellular localization could be

assigned (Supplemental Fig 4B).

Fig 3. Validation of mitochondrial candidate proteins. Immunofluorescent analysis of tagged

candidate proteins of interest (POI) in *P. berghei* parasites (PBANKA_ID indicated vertically).

POI were stained with anti-HA antibody (red, first column), mitochondria were stained with

anti-GFP antibody binding to the organelle marker (Mito, green, second column). The DNA

was stained with DAPI (blue in merge). (A) Representative images of candidate proteins
tagged with a mOrange-3xHA tag, imaged on a SP8 confocal microscope (Leica). (B-C)
Representative images of candidate proteins tagged with a linker-3xHA tag, imaged on a
LSM900 confocal microscope (Zeiss). (C) Images with the brightest signal for three lowly
expressed candidate proteins. Pixel intensities of the POI and mitochondrial signal were
normalized and plotted over the line indicated in the merge panel. Scale bar, 2 µm.

New mitochondrial proteins. A categorical representation of the identified proteins (Fig 2C)
shows that 172 of the 445 proteins have a previous annotation of being mitochondrial as they
are either part of the gold standard, have a mitochondrial GO term, or are described as
putative mitochondrial protein. A smaller number of proteins, 30, were part of the negative
set or have an apicoplast GO-term & no mitochondrial GO term. The remaining 243 proteins,
of which 121 proteins are annotated as conserved hypothetical proteins, contain new
mitochondrial candidates.

For 27 of the 121 conserved proteins with an unknown function, we found a
mitochondrial ortholog using the sensitive homology detection tool HHpred (36) that can
improve their annotation (Supplemental Table 2). For example, the human and yeast
orthologs of PF3D7_0306000 (Bayesian rank 41) are both cytochrome b-c1 complex subunit
8, making it very likely that the *Plasmodium* protein is also cytochrome b-c1 complex subunit
8, as confirmed by recent complexome profiling (12). Other similar examples include
PF3D7_1357600 (rank 285) that is likely a mitochondrial member of the 39S ribosomal protein
family L53, and PF3D7_1309900 (rank 80) that is likely succinate dehydrogenase assembly
factor 2.

Besides the possibility to improve annotations using well-characterized mitochondrial
orthologs, the predicted 445 proteins contain biologically interesting proteins that can add
new mitochondrial functions to *P. falciparum* and related species. Therewith, the prediction
provides targets for experimental research to uncover new biology. These proteins can be
divided into five categories: (i) proteins with known mitochondrial orthologs and an unknown
mitochondrial role in *P. falciparum*, (ii) proteins without a mitochondrial ortholog but with
homology to proteins with a known function and conservation of critical residues that suggest
conservation of that function, (iii) proteins with homology to proteins with a known function
from which residues known to be essential for catalytic activity or for binding substrates

residues have been lost, (iv) new proteins of a known mitochondrial protein family and (v)

proteins of a new mitochondrial protein family. Below, we describe several proteins per

category, including their domain structure, the conservation of active site residues, their

phylogenetic distribution and if available, the experimental confirmation of their

mitochondrial localization

Proteins with known mitochondrial orthologs and an unknown mitochondrial role in

P. falciparum

PF3D7_0413500/PfPGM2 (rank 111) contains a PGM domain and appears to be orthologous

to the human serine/threonine-protein phosphatase, PGAM5, of which the catalytic residue

H105 (61) is conserved (62). PfPGM2 catalyzes the dephosphorylation of phosphorylated

sugars and amino acids (62). In human cells, PGAM5 is localized to the mitochondrial outer

membrane (63) where it plays a role in apoptosis, mitofission, and mitophagy (reviewed in

(64)) among others via interactions with BCL2-like protein 1 (65). A previous study reported

an unexpected cytoplasmic localization of this protein in *P. falciparum* and *P. berghei*, though

in the absence of brightfield/DIC images or co-localization with marker proteins it is difficult

to draw conclusions on the localization (62). Therefore, we tagged the *P. berghei* ortholog

PBANKA_0715500 with a 3xHA tag and confirmed co-localization of PbPGM2 with our

mitochondrial marker (Fig 3B). We also observed a weak non-mitochondrial background

signal, which could indicate a potential dual localization. An important consideration in the

interpretation of the previously reported localization of the GFP-tagged *P. berghei* protein is

our observation that the use of a big tag such as GFP can interfere with the localization of

mitochondrial proteins (Fig S5).

Originally, we flagged two additional proteins, PF3D7_0213200 (rank 169) and

PF3D7_0611300 (rank 171), as interesting due to potential homology to BCL2, based on

sequence similarity and a similar alpha-helical structure predicted with HHpred (36).

PF3D7_0213200 was assigned an apicoplast GO-term, but in our analysis is a potential

mitochondrial protein. Analysis with TMHMM (66) indicates that it probably is a

transmembrane protein with an in-out topology. The protein PF3D7_0611300 already was

assigned a mitochondrial GO-term based on a screening in *T. gondii* (67), but was, to our

knowledge, not confirmed as mitochondrial localized with experiments characterizing this

protein in *P. falciparum.* Although we rejected BCL2 homology for both proteins after a

detailed examination of the residues conserved in the BCL2 family, we confirmed the
mitochondrial localization of PF3D7_0213200 (PBANKA_0310100 in Fig 3A) and
PF3D7_0611300 (PBANKA_0109600 in Fig 3B). Indeed, complexome profiling revealed that
the latter is part of the ATP synthase complex (12).

Proteins with a non-mitochondrial homolog and conservation of critical residues
PF3D7_0913400 (rank 30) is homologous to the bacterial elongation factor P. Although
eukaryotes contain initiation factor 5A as a cytoplasmic elongation factor P homolog, this
protein family was until now not observed in mitochondria. PF3D7_0913400 contains both
the N-terminal KOW-like domain and the central P/YeiP domain of elongation factor P, but
not the C-terminal OB domain. Elongation factor P plays a role in translation elongation and
specifically in the translation of stretches of 2 or more prolines (68). A basic residue at position
34 of elongation factor P (numbering from the *Escherichia coli* PDB structure 3A5Z_F (69))
that after post-translational modification interacts with the CCA-end of the tRNA, is
conserved in PF3D7_0913400. Notably, mitochondrial encoded *P. falciparum* cytochrome C
oxidase subunit 1 contains a proline pair at position 135-136, making it a potential target for
elongation factor P.

PF3D7_0812200 (rank 147) is homologous to the bacterial DegP protease family. It
contains both a serine endoprotease domain and a PDZ domain. The DegP from *E. coli*
functions in acid resistance in the periplasm. It is able to refold after acid stress and
subsequently can cleave proteins misfolded due to acid stress (70). The active site residue
(S210 in PDB structure 1KY9 (71)) is conserved in PF3D7_0812200, but residues involved in
allosteric loop interactions, including R187 are not. Orthologs of PF3D7_0812200 appear,
among the eukaryotes, limited to the Apicomplexa and Chromerida.

PF3D7_0503900 (rank 246) has a C-terminal dioxygenase domain (E= 1.3E-16). The
closest homolog in human is the phytanoyl-CoA dioxygenase that resides in the peroxisome,
an organelle absent from *Plasmodium*, where it is involved in α-oxidation of branched-chain
fatty acids. Important residues in the active site that are involved in iron binding, H175, H177,
H264 (72), are conserved in PF3D7_0503900, suggesting that it is a functional enzyme.
Nevertheless, levels of sequence conservation are low (14% identity with the human
phytanoyl-CoA dioxygenase) and we did not detect conservation of substrate binding sites

with the phytanoyl-CoA dioxygenase. The co-localization analysis suggested a mitochondrial
localization for PF3D7_0503900 (PBANKA_1103500 in Fig 3C).

PF3D7_1121500 (rank 307) contains a papain-like NLpC/P60 superfamily domain
(Peptidase_C92 in PFAM). This protein family contains, among others, cysteine peptidases
and amidases. Of the four residues essential for activity in BcPPNE from *Bacillus cereus* (73),
the most similar experimentally characterized homolog of PF3D7_1121500, three are
conserved (H49, E64, and Y164).

Proteins with homology to proteins with a known function from which residues known to be
essential for catalytic activity or for binding substrates residues have been lost
PF3D7_1004900 (rank 212) is homologous to the protein component of the signal recognition
particle (SRP), a ribonucleoprotein that recognizes and targets specific proteins to the ER in
eukaryotes. PF3D7_1004900 contains the C-terminal M domain (E= 5.8E-25), but not the
other, SRP54 and SRP54_N domains of this protein. In SRP the M domain binds both the SRP
RNA and the signal sequence of the target protein. Inspection of individual amino acids did
not reveal conservation of RNA binding amino acids, e.g. the arginines in helix M4 of the M
domain (74), are not conserved, but did reveal some conservation of hydrophobic amino acids
lining the groove in which the signal peptide is located. These hydrophobic amino acids have
been implicated in interactions with the signal peptide, specifically V323, I326, L329 in the
M1 helix and L418 in the M5 helix (positions relative to *Sulfolobus solfataricus* structure 3KL4
(74, 75)), suggesting a possible conservation of interaction of PF3D7_1004900 with a
hydrophobic α-helix. We experimentally confirmed the mitochondrial location of
PF3D7_1004900 (PBANKA_1203200 in Fig 3A).

PF3D7_1246700 (rank 223) is a member of the pyridoxamine 5'-phosphate oxidase
(PNPOx) like protein family that, besides pyridoxamine 5'-phosphate oxidase, also contains
the general stress protein 26 family. The most similar experimentally characterized protein is
general stress protein 26 from *Xanthomonas citri* encoded by gene *Xac2369*. The latter binds
FAD and FMN but not pyridoxal 5'-phosphate, indicating that it does not function as a PNPOx
(76). Relative to the unpublished structure of a protein from this family from *Nostoc*
punctiforme (PDB: 2I02), that does contain an FMN, we did not observe conservation of the
amino acids like W111, that line the FMN binding pocket, casting doubt of a function of
PF3D7_1246700 that includes the binding of FMN.

New members of mitochondrial protein families

PF3D7_1417900 (rank 109), PF3D7_1142800 (rank 172) and PF3D7_0927100 (rank 249) potentially contain a CHCH domain. They all have two pairs of cysteines that are very well conserved among their detectable homologs, and the nine amino acids between the cysteines are predicted to form an α-helix (36). Nevertheless, as nothing else but the cysteines appears to be conserved, the E-value with the PFAM CHCH domain entry, or with any known mitochondrial protein, is not significant (E>0.01). Jackhmmer analysis (77) detects homologs among the Apicomplexa, including a homolog in *Cryptosporidium muris*, but not outside this taxon. Known proteins with a CHCH domain are localized to the mitochondrial intermembrane space where they can participate in disulfide bond formation, suggesting that PF3D7_1417900, PF3D7_1142800, and PF3D7_0927100 might also be in the intermembrane space. Complexome profiling revealed that the first two are part of the ATP synthase complex (12). We tested PF3D7_1417900 and PF3D7_0927100 experimentally and confirmed them to be mitochondrial (PBANKA_1024800 and PBANKA_0827900 in Fig 3B respectively). Thus, based on our data and the complexome profiling data all three proteins are confirmed to be mitochondrial, increasing their likelihood that they indeed contain a CHCH domain.

Plasmodium contains a cytochrome C heme lyase (PF3D7_1224600, rank 129) and a cytochrome C1 heme lyase (PF3D7_1203600, rank 225), which are both essential during blood-stage development and have non-overlapping functions (78). We uncovered a third homolog in this family at rank 190, PF3D7_1121200 (E=0.0096, HHpred (36)). Although the homology covers domains II, III, and IV of heme lyases, of which domain II has been implicated in binding Heme (79), residues that have been implicated in heme binding, like H154 (coordinates for human protein (79)) and residues of domain I are not conserved in PF3D7_1121200. The protein also occurs in ciliates and dinoflagellates but has no orthologs outside of those taxa and therewith appears to be an alveolate-specific duplication.

A new Apicomplexan mitochondrial protein family

We assessed to what extent *Plasmodium* mitochondrial proteins were part of families with multiple mitochondrial members that resulted from duplications (Supplemental Table 2). Such "intra compartmental protein duplications" have also increased the size of the human mitochondrial proteome (37). Among the mitochondrial homologs, we uncovered a new

family in the Apicomplexa that in *Plasmodium* species has four representatives:

PF3D7_0821900 (rank 209), PF3D7_1336100 (rank 258), PF3D7_1134400 (rank 280), and

PF3D7_1228000 (rank 499). The family is characterized by a well-conserved WPP motif at its

N-terminus (Supplemental Fig 7), and we therefore name it the WPP family. Although

PF3D7_1228000 does not rank sufficiently high to fall within the 25% cFDR cut-off, all proteins

of the family are likely mitochondrial given their overall high ranking and the tendency of

members of protein families to be localized in the same cellular location. For the protein

family itself, we did not detect homologs outside the Apicomplexa and *Vitrella*. In several

species including *Plasmodium coatneyi* (PCOAH_00054040), *Babesia bovis* (BBOV_III010100),

and *Theileria orientalis* (MACL_00002472), the ortholog of PF3D7_1228000 is predicted to be

fused with an rRNA pseudourydilate synthase hinting at a potential function of this family in

rRNA maturation. Nevertheless, there are no experimental data supporting those gene

fusions. We unequivocally confirmed the mitochondrial location of PF3D7_0821900

(PBANKA_0708900 in Fig 3B) and the co-localization analysis also suggested a mitochondrial

localization for PF3D7_1336100 and PF3D7_1134400 (PBANKA_1350000 and

PBANKA_0914000 in Fig 3C respectively). PF3D7_1228000 was excluded from the analysis

due to low transcript levels.

Discussion

In this work, we ranked all nuclear encoded proteins of *P. falciparum* for their likelihood of

being mitochondrially targeted and defined the top 445 proteins (cFDR 25%) as likely

mitochondrial proteins (Supplemental Table 2). Despite the large variation between the

datasets in the coverage of the nuclear encoded proteome and in the ability to identify

mitochondrial proteins (Table 1, Fig 1), the probabilistic approach we used was able to

integrate the data in an unbiased way by assessing the distribution of gold standard genes

within each dataset during the scoring process.

Quality of the predictions. Several observations indicate the high quality of the predictions.

Firstly, the 10-fold cross-validation with an area under the curve of 0.959 shows the high

predictive value and robustness of the prediction. Secondly, almost half of the predicted

proteins have a previous annotation of being mitochondrial, even though most of these were

not used in weighing the datasets. Thirdly, of thirteen proteins that we set out to validate

experimentally, the seven for which we obtained a high enough expression to convincingly
locate them in the cell, were all mitochondrial, while for three others the experimental data
was consistent with a mitochondrial localization but equivocal due to low expression levels.
Fourth, even though our top 445 contains nine proteins of the negative gold standard that
was not manually supervised for all entries, manual examination of those nine showed that
the majority are likely mitochondrial after all. Seven of them were detected in the hyperLOPIT
study (22) and of those five were annotated as mitochondrial (legend Supplemental Table 2).
Finally, several proteins that we predicted to be mitochondrial have, since we made those
predictions, been shown to be mitochondrial using other methods. Specifically, complexome
profiling of mitochondria-enriched fractions has elucidated the composition of mitochondrial
complexes II, III, IV, and V (12). We identify in our top 445 proteins, six out of the seven
members of complex II (four of which not in the GS or mitochondrial in Gene Ontology (GO)),
ten out of the eleven members of complex III (none of which in the GS, three not in GO),
seventeen out of the nineteen members of complex IV (none of which in the GS, thirteen not
in GO), and twenty-one of the twenty three members of complex V (fifteen of which not in
the GS, nine not in GO, Supplementary Tables 2 and 5). These results reinforce the robustness
of the predictions and that the ranked list of the complete nuclear encoded *P. falciparum*
proteome, which we name PlasmoMitoCarta, is a useful resource for *Plasmodium*
researchers.
696
New mitochondrial biology. The results of the integration provide ample material for
exploring new mitochondrial biology as 185 out of the 445 proteins do not have a detectable
mitochondrial ortholog in yeast, human, or plant. Some, however, do have homologs in
bacteria that include conservation of critical residues, for example, the elongation factor P
whose function, if confirmed, would be unique to mitochondria. They also include paralogs
of the known mitochondrial proteins, like the twin Cx9C and heme lyase families, and a new
mitochondrial protein family that contains a well-conserved WPP motif. Finally, they include
PfPGM2, a protein that does have a human mitochondrial ortholog, but for which the
experimental data thus far had however pointed to a cytoplasmic organization (62). The
integrated 'omics data and localization with a 3xHA tag do point at a mainly mitochondrial
localization for a protein that in human is involved in apoptosis, mitofission, and mitophagy,

processes about which little is known in *Plasmodium.* Such proteins provide leads to new

mitochondrial biology.

As part of this study, we provide two other valuable resources. First, we included the

ortholog information gathered for this study that can improve the annotation of *P. falciparum*

proteins and provide researchers with additional hints for the function of a protein

(Supplemental Table 2). In addition, the WICCA tool that we developed for this study is

available online. It allows any researcher to assess co-expression of *P. falciparum* genes with

a set of genes of four *Plasmodium* species across data from 83 microarray expression

experiments, by weighing the datasets for their relevance to the set of genes. This can aid in

the discovery of novel members of known pathways and molecular systems.

Size of the mitochondrial proteome. We predict 445 mitochondrial proteins at the cut off,

set at cFDR 25%. When using the posterior probabilities (2^mitochondrial score) of all *P.*

falciparum genes to calculate the estimated number (E) of mitochondrial proteins by

summing them all up (E=sum($P_{posterior}$/($P_{posterior}$+1), see ref (80) for a detailed explanation), we

predicted the total size of the mitochondrial proteome to be 454 proteins. It therefore would

appear that our prior odds of ~10%, which affects the total size calculation, overestimated

the number of mitochondrial proteins. One can in principle lower the prior odds (see ref (80))

to 8.3% (412 proteins) such that the number is consistent with the estimated size of the

proteome based on all data. However, the presence of five likely mitochondrial proteins in

our gold negative sets leads to an underestimate of the size of the mitochondrial proteome.

We decided not to manually weed out these inconsistencies, as this cannot be done

systematically for all datasets, and applying this only to the apparent inconsistencies would

result in circular arguments.

The predicted total size of 454 proteins is relatively small compared to the

mitochondrial proteomes in human, plant, and yeast that consist of at least 900 proteins (5,

39, 40). However, small mitochondrial proteomes have been reported before, for example,

573 proteins in the distantly related ciliate *Tetrahymena thermophila* (81). In agreement with

our findings, a recent study on the mitochondrial proteome of *T. gondii* that was not included

in our integration reports a proteome of 421 proteins (16).

In conclusion, we combined the information of eight datasets with the curated gold standards

to rank all nuclear encoded *P. falciparum* proteins on their likelihood of being mitochondrial

in PlasmoMitoCarta. The value of this ranked proteome is shown by *in vivo* validation of top

scoring proteins in the closely related species *P. berghei* and will provide an important

resource for future investigations.

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Competing interests

The authors declare no competing interests.
758

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760

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