

Bacterial amino acid auxotrophies enable energetically costlier proteomes 1

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Abstract 10

The outsourcing of amino acid (AA) production to the environment is relatively common 11
across the tree of life. We recently showed that the massive loss of AA synthesis capabilities in 12
animals is governed by selective pressure linked to the energetic costs of AA production. 13
Paradoxically, these AA auxotrophies facilitated the evolution of costlier proteomes in animals 14
by enabling the increased use of energetically expensive AAs. Experiments in bacteria have 15
shown that AA auxotrophies can provide a fitness advantage in competition with prototrophic 16
strains. However, it remains unclear whether energy-related selection also drives the evolution 17
of bacterial AA auxotrophies and whether this affects the usage of expensive AAs in bacterial 18
proteomes. To investigate these questions, we computationally determined AA auxotrophy 19
odds across 980 bacterial genomes representing diverse taxa and calculated the energy costs of 20
all their proteins. Here, we show that auxotrophic AAs are generally more expensive to 21
synthesize than prototrophic AAs in bacteria. Moreover, we found that the cost of auxotrophic 22
AAs significantly correlates with the cost of their respective proteomes. Interestingly, out of 23
all considered taxa, *Mollicutes* and *Borreliaceae*—chronic pathogens highly successful in 24

immune evasion—have the most AA auxotrophies and code for the most expensive proteomes. 25
These findings indicate that AA auxotrophies in bacteria, similar to those in animals, are shaped 26
by selective pressures related to energy management. Our study highlights bacterial AA 27
auxotrophies as costly outsourced functions that allowed bacteria to more freely explore protein 28
sequence space. It remains to be investigated whether this relaxed use of expensive AAs also 29
enabled auxotrophic bacteria to evolve proteins with improved or novel functionality. 30

Keywords: bacteria; amino acids; auxotrophy; energetics; synthesis; selection; evolution; 31
functional outsourcing 32

Introduction 33

The concept of functional outsourcing posits that organisms streamline their genomes by losing 34
costly functions that can be substituted through external biological interactions [1]. This 35
principle clearly applies to the outsourcing of amino acid (AA) production, a phenomenon 36
observed widely across the tree of life [1–5]. A particularly striking example is animals, which 37
almost universally lack the ability to synthesize about half of the proteinogenic AAs [2,5]. 38
Recent research demonstrates that this phenomenon is driven by selective pressure related to 39
the high energy cost of AA production, enabling animals to evolve costlier proteomes that 40
incorporate expensive AAs more frequently [5]. These findings raise the possibility that similar 41
correlations between proteome energetics and AA biosynthetic capabilities exist in other major 42
clades on the tree of life, including bacteria. 43
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Compared to animals, the understanding of bacterial AA biosynthesis remains relatively 45
incomplete. Earlier studies indicated that most bacteria possess at least a few auxotrophies 46
[6,7]. However, recent research has revealed that the prevalence of AA auxotrophies may have 47
been overestimated due to gaps in knowledge regarding bacterial biosynthetic pathways, 48
though many bacteria still lack the ability to synthesize the full set of AAs [4,8]. Experimental 49
evidence shows that AA auxotrophies can confer a fitness advantage in competition with 50

prototrophic strains [7,9], and they may serve as an evolutionary strategy to reduce biosynthetic 51
burdens via cooperative interactions within microbial communities [10]. 52

The adaptive benefits of AA auxotrophies in bacteria remain under debate. D'Souza & Kost 53
[9] speculated that outsourcing AA biosynthesis might reduce cellular metabolic costs. While 54
it is well-established that AAs differ in their biosynthetic costs [10–12] and that costlier AAs 55
foster stronger microbial cross-feeding interactions [10], a recent study found no significant 56
correlation between AA biosynthesis costs and the prevalence of AA auxotrophies among 57
bacteria [4]. However, alternative approaches could be employed to rigorously test whether 58
energy-related selection drives the evolution of AA auxotrophies. For instance, if such selection 59
influences the loss of AA biosynthetic capabilities, it should also manifest in the integration of 60
more expensive AAs into bacterial proteomes [5]. To our knowledge, no study has yet 61
examined bacterial proteome energetics in this context. 62

Detecting auxotrophies is itself an active area of research, employing various methodologies. 63
Many rely on *in silico* approaches, including genome-scale metabolic modeling [13,14] or 64
homology-guided annotation of enzymes [4,7,15]. These computational approaches are 65
typically validated against a limited number of datasets obtained by experiments [4,14]. 66
However, no simple and standardized protocol currently exists for comparing AA auxotrophy 67
estimates across studies. 68

To address these gaps, we assembled a taxonomically diverse dataset of bacterial proteomes 69
and analyzed whether AA biosynthesis costs can explain trends in AA auxotrophy composition. 70
Using a simple methodology for auxotrophy detection based on MMseqs2 clustering, we 71
achieved results comparable in quality to those of previous approaches. Our findings reveal 72
that more expensive AAs are more frequently lost and that bacteria with greater numbers of 73
expensive AA auxotrophies encode costlier proteomes, paralleling patterns observed in 74
animals. These results suggest that energy-driven selection plays a key role in shaping 75
auxotrophic phenotypes in bacteria, allowing them to explore protein sequence space more 76
freely during evolution. 77

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Results

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To uncover global trends in the evolution of bacterial auxotrophies, we compiled a database of 980 high-quality proteomes representing the diversity of bacteria (Table S1). We assessed the completeness of amino acid (AA) biosynthesis pathways in these species using a MMseq2 clustering approach [16]. This method clusters, in a single step, a representative sample of bacterial enzymes known to catalyze reactions in AA biosynthesis pathways together with all proteomes in our database (see Materials and Methods). Based on the composition of the recovered clusters, functional information on the AA anabolism is then transferred between cluster members allowing us to determine the completeness of 20 AA biosynthesis pathways for each species. Unlike previous studies that rely on strictly defined cutoff values to designate auxotrophies—thereby losing part of the available information—we analyzed the pathway completeness values directly. This approach provides a more accurate representation of the odds that a particular pathway is present.

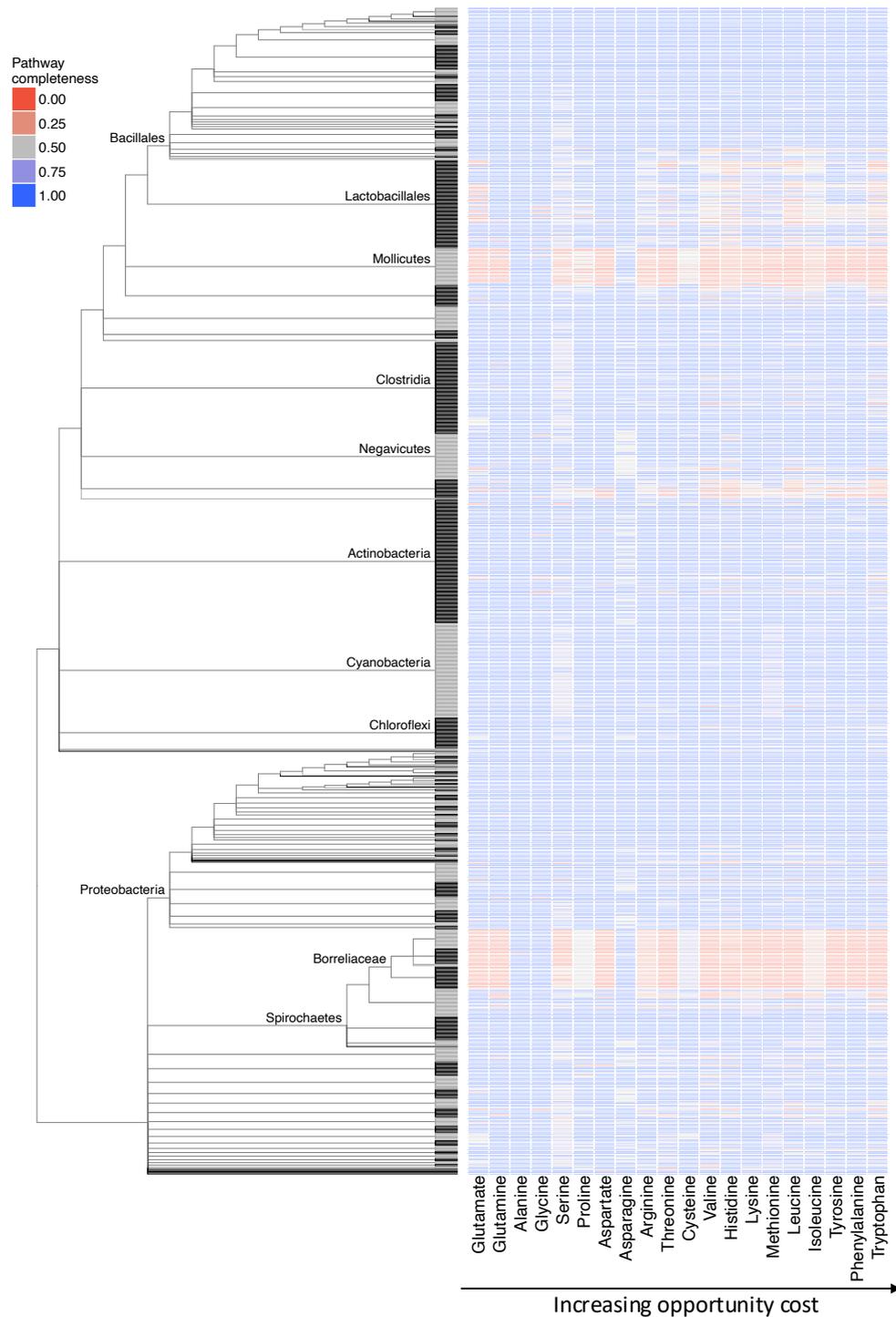
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For each of the twenty amino acids, completeness scores range from 0 to 1, where 0 indicates that all enzymes in the pathway are absent, and 1 indicates that all enzymes are present in a given species (Fig. 1, File S1). We found that the total pathway completeness for the 20 amino acids has an average value of 17.33, with a median of 19.5, for the whole dataset. Consistent with these values, nearly 66% of the species in our dataset exhibit total pathway completeness above 19. These high completeness values suggest that many bacteria are prototrophic for most amino acids, aligning with findings from recent studies [4,8]. However, certain taxonomic groups—including Lactobacillales, *Mollicutes*, and Borreliaceae—show a significant reduction in multiple amino acid biosynthetic pathways (Fig. 1, File S1), indicating that auxotrophies are common in these groups.

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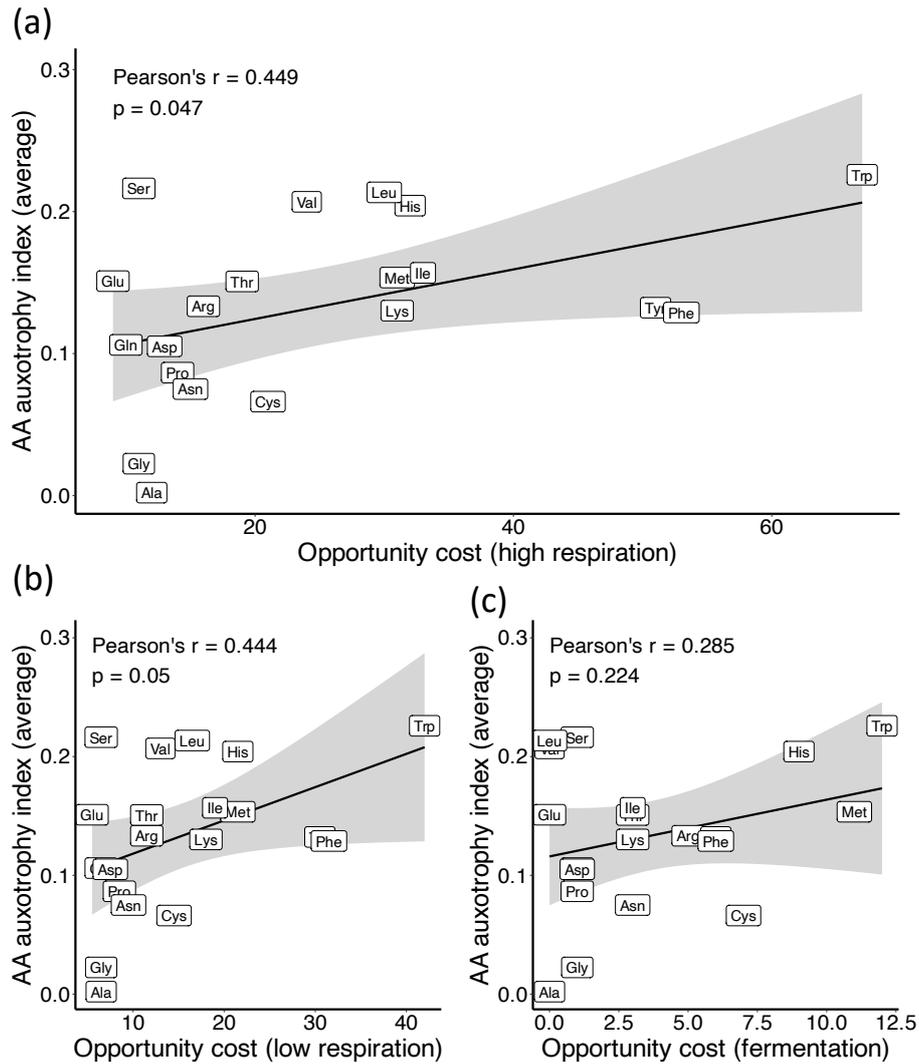
Figure 1. Completeness of AA biosynthesis pathways in bacteria. We created a database of 980 bacterial species to get a comprehensive overview of AA dispensability in this group. Fully resolved tree is shown File S1. We retrieved data on enzymes involved in AA biosynthesis pathways from the KEGG and MetaCyc databases. We searched for their homologs within our

reference database using MMseqs2 clustering (see Methods). For each AA, we showed a 110
completeness score, which represents the percentage of enzymes within a pathway that returned 111
significant sequence similarity matches to our reference collection of AA biosynthesis 112
enzymes. In the case of AAs with multiple alternative pathways, we showed the results only 113
for the most complete one. 114

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If energy-driven selection generally influences the evolution of bacterial amino acid (AA) 116
auxotrophies, one would expect that the ability to synthesize energetically expensive AAs is 117
more frequently lost. To test this hypothesis, we devised an AA auxotrophy index (AI), defined 118
as 1 minus the completeness score, and compared it against the opportunity cost [5], which 119
estimates the energy expenditure associated with AA synthesis (see Materials and Methods). 120
We observed a significant moderate correlation between opportunity cost and auxotrophy index 121
when opportunity cost values for respiratory metabolism were applied (Fig. 2A, B). However, 122
under fermentative conditions, this correlation was much weaker and not statistically 123
significant (Fig. 2C). Together, these findings suggest that the evolution of AA auxotrophies in 124
bacteria, similar to animals, is generally driven by selection favoring energetic savings during 125
AA synthesis, a pattern most pronounced under respiratory conditions. 126

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Figure 2. Correlation between AA biosynthesis cost and the average AA auxotrophy index. We estimated the AA auxotrophy index (AI), a measure which equals one minus completeness score, for 980 bacterial species and calculated the average value for each AA. We correlated this value with the opportunity cost of each AA, calculated for three different respiratory modes (see Materials and Methods). Pearson correlation coefficient and p-value are shown on the graph.

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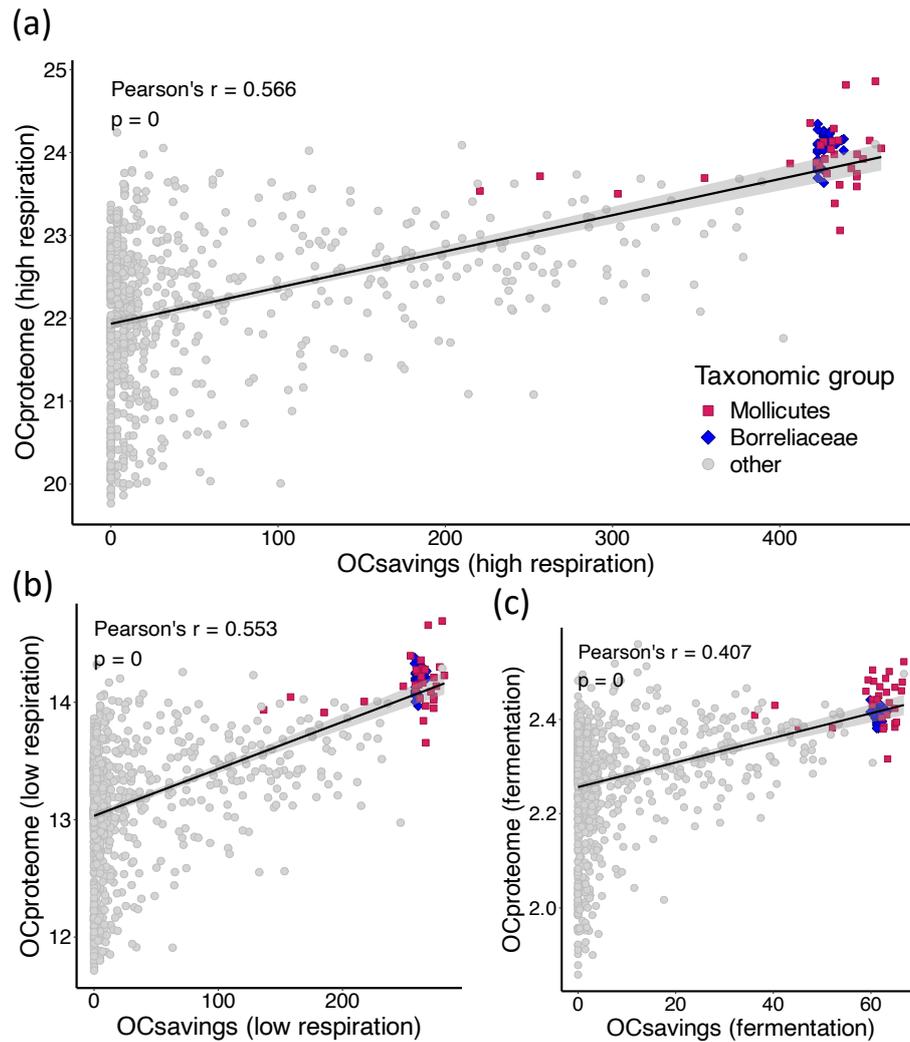
However, the central question remains how these reductions in AA biosynthetic pathways influence overall proteome energetics. If energy-driven selection underpins the evolution of

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AA auxotrophies in bacteria, one would expect auxotrophic species to maintain more expensive proteomes than their prototrophic counterparts. This is because auxotrophs consume considerably less energy on AA biosynthesis and acquire the missing AAs at a relatively low cost from the environment. In essence, this pattern would suggest that the energy saved on the synthesis of costly AAs offsets part of the proteome's energy expenditure, enabling auxotrophs to incorporate more expensive proteins, potentially contributing to novel functions [5].

To test this idea, we calculated the opportunity cost of an average amino acid (AA) for each bacterial proteome ($OC_{proteome}$) as well as the overall biosynthetic cost savings achieved through AA auxotrophy ($OC_{savings}$, see Materials and Methods). These calculations were performed across three respiratory modes: fermentation, low respiration, and high respiration [5]. We then assessed the correlation between $OC_{proteome}$ and OC_{saving} (Fig. 3). Regardless of the respiratory mode used to estimate energy expenditure, our results showed that species achieving the greatest energy savings in AA production also maintain the most expensive proteomes. Similar to animals, bacterial auxotrophies appear to influence not only the immediate energy budget related to AA production but also reduce selective pressure against the use of energetically costly AAs in proteomes.

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Figure 3. Correlation between the cost of an average AA per proteome and the amount of outsourced energy for AA biosynthesis. We estimated the AA biosynthesis pathway completeness for 980 bacterial species. For each proteome, we calculated its opportunity cost (OC_{proteome}) by calculating for each AA the product of its opportunity cost and its frequency in the proteome and then by taking the sum of the obtained values (see Materials and Methods). For each species, we also estimated the energy that was saved by outsourcing AA biosynthesis (OC_{savings}). To obtain this value we first multiplied auxotrophy index with opportunity cost for every AA and then we summed the obtained values for all 20 AAs (see Materials and Methods). We repeated all calculations for three different respiratory modes. Pearson correlation coefficient (r) and p-value are shown on the graph.

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Discussion

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In our previous work, we applied the concept of functional outsourcing [1] to AA biosynthesis 168
in animals and developed a model describing the conditions necessary for the evolution of AA 169
auxotrophies [5]. This model predicts that the loss of AA biosynthetic pathways is selectively 170
favored in respiring organisms with abundant environmental availability of AAs. Crucially, the 171
loss of AA production capabilities is not random—energy-optimizing selection favors the loss 172
of pathways for energetically costly AAs. This, in turn, enables auxotrophs to more freely 173
explore protein sequence space by reducing selective constraints on the use of expensive AAs 174
in their proteomes [5]. To test the broader validity of this model across major clades, we 175
investigated the patterns of AA auxotrophies in bacteria. 176

While animals exhibit nearly identical sets of auxotrophies among each other, bacterial 177
metabolisms are far more diverse, making bacterial auxotrophies more challenging to detect 178
and interpret [4,7,8]. Although it is known that AA auxotrophies can confer a fitness advantage 179
in competition with prototrophic strains [7,9], it was unclear whether this advantage arises 180
solely from the immediate increase in available energy or if, in the long run, it also influences 181
proteome composition [5]. 182

Our results reveal a significant positive correlation between the AA auxotrophy index averaged 183
across tested bacteria and the AA opportunity cost, as predicted by the AA outsourcing model 184
[5]. This finding aligns with earlier observations that costlier AAs promote stronger microbial 185
cross-feeding interactions [10] and that AA auxotrophies confer a fitness advantage [7,9]. Apart 186
from our study, only one prior investigation has explicitly examined bacterial AA auxotrophies 187
from an energetics perspective, reporting no significant correlation between the frequency of 188
an AA being auxotrophic and its biosynthetic cost [4]. 189

The reasons for this discrepancy are unclear and may stem from differences in bacterial genome 190
datasets, auxotrophy detection pipelines, or biosynthetic cost estimates. Thus, to further test 191
the robustness of our findings, we analyzed data from another comparable study that calculates 192

AA auxotrophies across the bacterial tree of life using metabolic modeling but lacks energetic 193
calculations [14]. Similar to our study, this dataset also exhibited a significant correlation 194
between the frequency of an AA being auxotrophic and its biosynthetic cost (Figure S1), with 195
an even higher correlation coefficient than observed in our results. Collectively, these findings 196
suggest that, in at least some bacterial groups, AA auxotrophies are influenced by energy 197
savings at the level of AA biosynthesis. 198

The second prediction of our model is that bacterial species with more auxotrophies should 199
have more expensive proteomes. Our results confirm this prediction, showing that auxotrophic 200
species indeed maintain more expensive proteomes. This finding indicates that AA auxotrophy 201
fundamentally influences proteome composition. The energy savings achieved through the 202
outsourcing of AA biosynthesis relax the constraints on the incorporation of costly AAs into 203
the proteome, thereby enabling auxotrophic organisms to explore protein sequence space more 204
freely [1,5,17–19]. 205

Based on these findings, we hypothesize that the increase in the frequencies of costly AAs in 206
auxotrophic species' proteomes could result in the evolution of proteins with novel functions 207
[1,5,17–19]. Interestingly, the most auxotrophic groups with the most expensive proteomes in 208
our analysis are *Mollicutes* and *Borreliaceae*, the members of which are notorious for causing 209
severe infections that are difficult to manage [20–22]. It is also known that *Borrelia* (*syn.* 210
Borrelia) *burgdorferi* (Spirochaetales) harbors many *Borreliaceae*-specific genes with 211
unknown functions, which may be implicated in the development of Lyme disease [23]. The 212
evolution and function of these novel genes may be explainable in terms of auxotrophy-related 213
energetic shifts, which should be explored in future studies. 214

In conclusion, our results suggest a global macroevolutionary trend where AA biosynthesis 215
capability is shaped by energy-saving selection, ultimately leading to the evolution of more 216
expensive proteomes. However, bacteria exhibit remarkable ecological and metabolic diversity, 217
thriving in an array of physically and chemically unique habitats [8,24,25]. This diversity raises 218
the possibility that factors beyond energetic costs influence reductions in AA biosynthetic 219

pathways. Future studies focusing on specific bacterial lineages and ecologies will be crucial 220
to uncover the role of such factors in shaping the evolution of AA biosynthetic capabilities. 221

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Materials and Methods 223

To create the database of bacterial proteomes (Table S1), we combined datasets previously 224
assembled for the phylostratigraphic analyses of *Bacillus subtilis* [26] and *Borrelia burgdorferi* 225
[23], along with a resolved phylogeny of *Escherichia coli*. This resulted in a database of 980 226
species representing most major bacterial lineages. The proteomes, primarily retrieved from 227
the NCBI database and supplemented by the Ensembl database, were evaluated for 228
contamination using BUSCO [27], and all were confirmed to be free of contamination [1]. 229

In our previous study [5], we retrieved pathways and enzyme codes involved in amino acid 230
(AA) biosynthesis from the KEGG and MetaCyc databases. For Aas that can be synthesized 231
via multiple alternative pathways, we treated each pathway separately, even when they shared 232
some enzymes. Using this collection of enzyme codes associated with AA biosynthesis, we 233
retrieved bacterial protein sequences from the KEGG database [28]. For each genus with 234
representatives annotated in KEGG, we selected the species with the largest number of 235
enzymes catalyzing reactions in AA biosynthesis pathways. This process resulted in a protein 236
sequence reference database comprising 387,892 enzymes across 2,095 species (Table S2). 237

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In the next step, we combined the downloaded enzyme sequences known to be involved in 239
amino acid (AA) biosynthesis pathways with all sequences from our bacterial proteomes 240
(4,230,625 sequences across 980 species) into a single database. We then clustered this 241
combined database using MMseqs2 [16] with the following parameters: -cluster-mode 0, -cov- 242
mode 0, -c 0.8, and -e 0.001. Clustering with these parameters generated clusters whose 243

members exhibit highly similar architectures, as the alignment between query and target 244
sequences covered at least 80% of their length [1]. 245

Based on the presence of enzymes involved in AA synthesis, we functionally annotated the 246
remaining members of the respective clusters. For each AA biosynthesis pathway and species 247
in the database, we calculated a pathway completeness score (i.e., prototrophy index) by 248
dividing the number of detected enzymes by the total number of enzymes in that pathway, 249
resulting in values ranging from 0 to 1. If a species contained alternative biosynthetic pathways 250
for an AA, the pathway with the highest completeness score was selected. We then calculated 251
the AA auxotrophy index (AI_i) using the formula: 252

$$AI_i = 1 - \text{completeness score} \quad 253$$

In this formula i denotes one of 20 AAs ($i = 1, \dots, 20$). 254

To evaluate the performance of our method, we utilized a previously established testing set of 255
experimentally identified prototrophies and auxotrophies [4,14] to estimate pathway 256
completeness scores. The first tested dataset comprised 160 fully prototrophic species [4]. Our 257
approach exhibited an error rate of 0.012, indicating that approximately 1.2% of amino acids 258
were incorrectly identified as auxotrophic (Data S1). The second dataset included 15 species 259
with at least one known auxotrophy [14]. In this case, we detected an error rate of 0.188 for 260
false prototrophs, meaning that around 19% of amino acids were incorrectly classified as 261
prototrophic (Data S2). Taken together, these error rates suggest that our approach to 262
auxotrophy detection is conservative and aligns with error rates reported for similar methods 263
[4,14]. 264

In our earlier study, we calculated the opportunity cost of biosynthesis for each AA depending 265
on the three respiration modes: high respiration, low respiration and fermentation [5]. The 266
opportunity cost is calculated as the sum of the energy lost in the synthesis of AAs (direct cost) 267
and the energy that would have been produced if a cell catabolized precursors instead of making 268
AAs [5]. This measure reflects the overall impact of AA synthesis on the cell's energetic budget. 269

Using the AA opportunity cost, we also calculated the opportunity cost of an average AA in each proteome ($OC_{proteome}$) using the following formula:

$$OC_{proteome} = \frac{\sum_{i=1}^{n=20} OC_i \times N_i}{\sum_{i=1}^{n=20} N_i} = \sum_{i=1}^{n=20} OC_i \times f_i$$

In this formula, OC_i represents the opportunity cost of a given AA, N_i denotes the total number of occurrences of this AA in the entire proteome, and f_i represents the frequency of the AA in the proteome (calculated as the number of occurrences of the AA divided by the total number of AAs in the proteome).

We also introduced a new measure to quantify the energetic savings of a species by linking the AA pathway completeness to the opportunity cost. This measure estimates the energy saved by outsourcing AA production to the environment, relative to the energy required to synthesize the full set of 20 AAs. It is calculated as follows:

$$OC_{savings} = \sum_{i=1}^{n=20} OC_i \times AI_i$$

In this formula, OC_i denotes the opportunity cost of a given AA, while AI_i denotes the AA auxotrophy index.

To calculate correlations, we used the `cor.test()` function in the R stats (v. 3.6.2) package. The heatmap was visualized using the `ggtree` R package [29].

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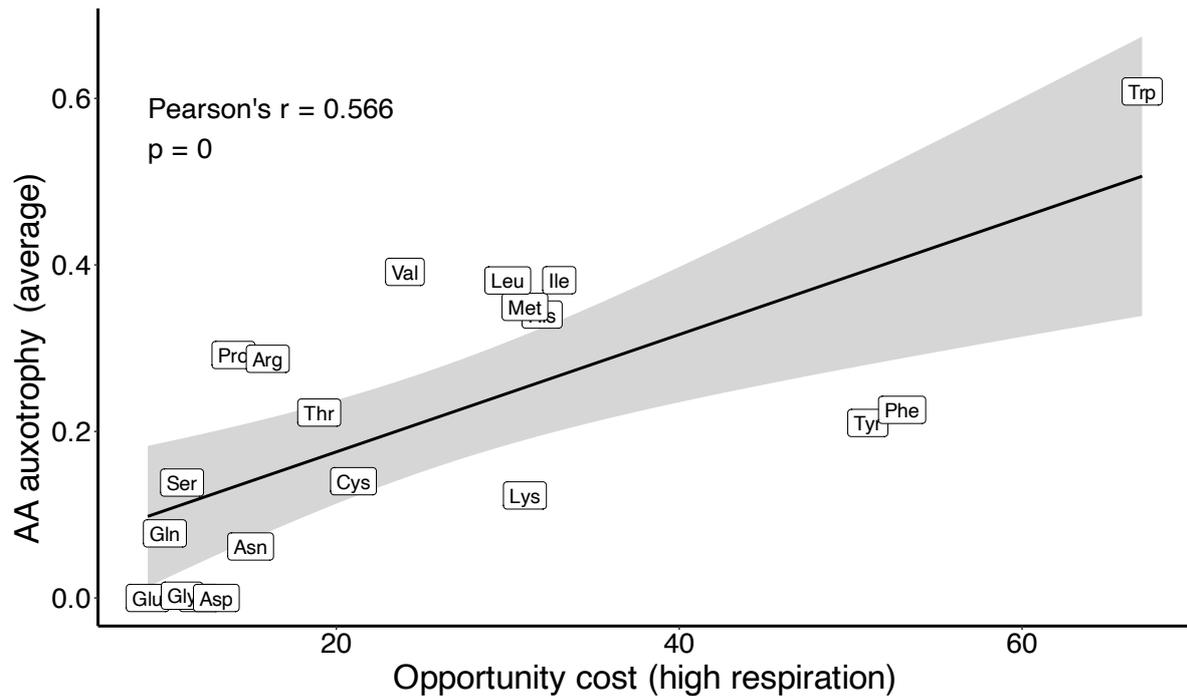


Figure S1. Correlation between AA biosynthesis cost and the average AA auxotrophy based on data from Starke et al. (2023). We calculated the average of AA auxotrophy measures provided in the Starke et al. (2023) study for 3687 bacterial species. We correlated this value with the opportunity cost of each AA, calculated for high respiration mode (see Materials and Methods). Pearson correlation coefficient and p-value are shown on the graph.