1 **Co-evolution of gene transfer agents and their alphaproteobacterial hosts**

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Abstract

Gene transfer agents (GTAs) are enigmatic elements that resemble small viruses and are known to be produced during nutritional stress by some bacteria and archaea. The production of GTAs is regulated by quorum sensing, under which a small fraction of the population acts as GTA producers, while the rest become GTA recipients. In contrast to canonical viruses, GTAs cannot propagate themselves because they package pieces of the producing cell's genome. In alphaproteobacteria, GTAs are mostly vertically inherited and reside in their hosts' genomes for hundreds of millions of years. While GTAs' ability to transfer genetic material within a population and their long-term preservation suggests an increased fitness of GTA-producing microbes, the associated benefits and type of selection that maintains GTAs are poorly understood. By comparing rates of evolutionary change in GTA genes to the rates in gene families abundantly present across 293 alphaproteobacterial genomes, we detected 59 gene families that likely co-evolve with GTA genes. These gene families are predominantly involved in stress response, DNA repair, and biofilm formation. We hypothesize that biofilm formation enables the physical proximity of GTA-producing cells, limiting GTA-derived benefits only to a group of closely related cells. We further conjecture that population structure of biofilm-forming sub-populations ensures that the trait of GTA production is maintained despite the inevitable rise of "cheating" genotypes. Because release of GTA particles kills the producing cell, maintenance of GTAs is an exciting example of social evolution in a microbial population.

Importance

Gene transfer agents (GTAs) are viruses domesticated by some archaea and bacteria as vehicles for carrying pieces of the host genome. Produced under certain environmental conditions, GTA particles can deliver DNA to neighboring, closely related cells. Function of GTAs remains uncertain. While making GTAs is suicidal for a cell, GTA-encoding genes are widespread in genomes of alphaproteobacteria. Such GTA persistence implies functional benefits but raises question about how selection maintains this lethal trait. By showing that GTA genes co-evolve with genes involved in stress response, DNA repair, and biofilm formation, we provide support for the hypothesis that GTAs facilitate DNA exchange during the stress conditions and present a model for how GTAs persist in biofilm-forming bacterial populations despite being lethal.

Introduction

Multiple bacteria and archaea produce Gene Transfer Agents (GTAs) – the viriforms whose function and mode of selection to maintain them remain unsolved ([1-3]). These domesticated virus-derived elements are encoded by genes in their host's genome and, when produced, resemble tailed double-stranded DNA (dsDNA) viruses (phages). In contrast to viruses, GTAs do not package the genes that encode them, and instead contain fragments of the producing host's genome ([1], [4-7]). Experimentally, GTAs are most studied and characterized in the alphaproteobacteria *Rhodobacter capsulatus* (RcGTA) and *Caulobacter crescentus* ([6], [8], [9]), but they are also produced by several additional bacterial and archaeal species ([10]). Many more prokaryotes encode GTA-like genes ([5], [11-18]), and the presence of GTA-like genes in almost 60% of publicly available alphaproteobacterial genomes ([19]) suggests that GTA production is more widespread than currently appreciated.

RcGTA production is a population-level phenomenon: it is triggered by nutrient depletion ([20]) and is regulated by quorum sensing ([21]). Only a small subset of the population acts as RcGTA producers; the remaining cells become recipients, by displaying specific polysaccharide receptors for RcGTAs adsorption ([22]) and expressing competence genes ([23]). Genetic pieces delivered by RcGTAs to a recipient cell can be integrated into the cell's genome via homologous recombination ([24]).

The benefits of GTA production and of acquiring GTA-packaged DNA in a microbial population are not fully understood. Since their discovery, GTAs were hypothesized to mediate DNA repair ([25]), and recently this hypothesis was confirmed by experimental demonstration of GTA-mediated DNA repair via homologous recombination in *C. crescentus* ([6]). Moreover, facilitation of DNA damage repair appears to improve the survival of *C. crescentus* populations

in nutrient limited conditions ([6](#)), possibly due to a reduction in mutational load. Beyond the

repair of already existing genes, released GTA particles could enable exchange of beneficial

traits in a microbial population ([8](#), [26](#)) and provide nutrients to surrounding cells as the

programmed cell death phenomenon does ([27](#), [28](#)), although these hypotheses remain to be

experimentally verified. Despite these putative population-level benefits, GTA-producing cells

lyse and therefore leave no progeny, making it impossible for selection that maintains GTA

production to act on the level of individual cells. Better understanding of GTA production and

reception cycle and of genes underlying it will likely help us elucidate ecological role of GTAs in

microbial communities, and details of the population-level selection that preserves the trait.

The RcGTA is encoded and regulated by at least 24 genes that are distributed across five

different loci ([29](#)). Seventeen genes are located in one locus that is commonly referred as the

head-tail cluster ([2](#)) (**Figure 1A**). The locus encodes the majority of structural proteins required

for the RcGTA particle assembly ([30](#)). Products of many additional "host" genes are critical for

the regulation of the RcGTA particle production, DNA uptake, and DNA integration. For

example, the CckA-ChpT-CtrA phosphorelay system, which controls the cell cycle and DNA

replication in other model organisms ([31-33](#)), modulates production of RcGTA particles and their

release ([34](#), [35](#)). Serine acetyltransferase (cysE1), which is required for biofilm formation, plays

a critical role for the optimal receipt of RcGTAs ([36](#)). Capsular polysaccharides, which serve as

RcGTA receptors, are synthesized under control of GtaR/I quorum-sensing genes ([22](#)).

Competence machinery proteins ComEC, ComF and ComM facilitate entry of DNA into cells

([23](#)). Integration of the incoming genetic material into the host genome via homologous

recombination is facilitated by DprA and RecA ([24](#)). It is likely that products of multiple other

"host" gene families important for the proper functioning of GTAs remain to be discovered, and

in this study we use a comparative genomics approach to search for such genes.

Genes that are involved in the similar molecular processes, or co-expressed together, tend

to co-evolve with each other ([37](#), [38](#)), and, vice versa, the protein-protein interactions can be

unveiled by finding co-evolving genes that encode the interacting proteins ([39](#), [40](#)). The co-

evolution among genes can be effectively identified via Evolutionary Rate Covariation (ERC)

approach ([37](#), [41](#), [42](#)). Evolutionary rate covariation measures the degree of correlation of

changes in evolutionary rates across the phylogenies of a pair of proteins, assuming that

functionally related proteins have similar selection pressures, resulting in coordinated changes in

substitution rates ([37](#), [38](#)). Because GTA head-tail cluster has resided within GTA-containing

alphaproteobacterial genomes for at least 700 million years ([13](#)) and, as mentioned above, GTA

production is tightly integrated into the molecular circuits of the GTA-carrying bacteria,

evolutionary rates of gene families involved in GTA lifecycle are expected to correlate with the

rates of the GTA genes.

Head-tail cluster genes are easily detectable across genomes in a large clade of

alphaproteobacteria ([11](#), [13](#)) and therefore provide a rich dataset for comparative analyses of

evolutionary rates. In this study, we examined the evolutionary rate covariation patterns of

protein-coding genes encoded in 293 representative alphaproteobacterial genomes that contain

either complete or nearly complete GTA head-tail clusters. We found that GTA head-tail cluster

genes co-evolve with 59 gene families, 55 of which have not been previously linked to GTAs.

Thus, we dramatically expand the list of genes that could be important for GTAs' functionality

and hence could provide insights into GTAs' role in bacterial populations. By combining our

findings with the existing knowledge about GTAs, we propose a model that explains persistence

of GTA production in bacterial populations.

Results

Alphaproteobacterial GTA genes co-evolve with each other

The ERC method was developed for and tested on eukaryotic genes ([37](#), [38](#)) and, to our

knowledge, has not been applied to bacterial genomes. Therefore, before using the approach to

identify genes co-evolving with GTA genes, we evaluated it on GTA genes found in the 293

alphaproteobacterial genomes. Because genes in the GTA head-tail cluster have a common

promoter ([8](#), [43](#)) and the gene products are functionally related (i.e., produce a GTA particle that

has DNA packaged into its head), we expected strong co-evolution among GTA genes. Indeed,

we found that 51 out of 55 possible pairs of the 11 reference GTA genes (see **Methods** for

definition) have significantly similar co-variation of evolutionary rates, as measured by the

Pearson's coefficient (p-value < 0.05 after Bonferroni correction). Each reference GTA gene co-

evolves with at least 7 other reference GTA genes, with 6 of them co-evolving with all 10 other

reference GTA genes (**Figure 1B**). These findings suggest that the ERC method adequately

identifies co-evolving genes in alphaproteobacterial genomes.

Co-evolving alphaproteobacterial genes encode functionally related proteins

Co-evolving genes of eukaryotes identified through ERC analyses were shown to be

either functionally related or involved in similar biological processes ([37](#), [38](#)). To examine how

robustly the ERC method can identify functionally related gene pairs in our dataset of

alphaproteobacterial genomes, we (i) evaluated rates of covariation within functional modules of

the GTA head-tail cluster and (ii) examined a relationship between co-evolution and literature-

and experiment-based functional inferences for a subset of gene families nearly universally

found across GTA-containing alphaproteobacteria.

GTA head-tail cluster encodes three modules that are responsible for distinct functional

stages of GTA production: DNA packaging, head morphogenesis, and tail morphogenesis (2, 29,

30) (**Figure 1A**). Phage genes within the same functional class are more likely to interact with

one another (44). We found that the Pearson's correlation coefficient is significantly higher (and,

therefore, co-evolutionary signal is significantly stronger) for reference GTA genes within each

module than between the reference GTA genes from different modules (Mann-Whitney U-test, p-

value = 0.002) (**Figure 1C**). These findings suggest that the strength of co-evolutionary signal

measured by the ERC analysis correlates with the degree of physical and functional interactions

among GTA genes.

Expanding our analysis beyond GTA genes, we examined protein-coding genes in a

model marine bacterium *Phaeobacter inhibens*, whose genome encodes the largest number

(1,370) of genes from 1,470 gene families nearly universally found across GTA-containing

alphaproteobacteria, and in *Caulobacter crescentus* and *Dinoroseobacter shibae*, which are

experimentally shown to produce GTAs (5, 6). The information about the interactions of most

proteins encoded by the protein-coding genes in the genomes of these bacteria is available in the

STRING database (45), and the experimental relative fitnesses of many genes are cataloged in

Fitness Browser (46). Using the ERC analysis on the 1,320, 1,199, and 1,255 genes, we

identified 10,514, 9,373 and 9,675 co-evolving gene pairs for *P. inhibens*, *C. crescentus*, and *D.*

shibae, respectively (**Figure S1**). The co-evolution networks, in which nodes correspond to

genes and edges designate the presence of significant evolutionary rate covariation (see FigShare

repository), are significantly similar to both the networks of the pairwise interactions of the

encoded proteins and the networks of fitness effects for all three genomes (p-value < 0.001,

permutation test) (**Figure 2**). Moreover, co-evolving genes are more likely to belong to the same

Clusters of Orthologous Groups (COG) category (assortativity of 0.096 for *P. inhibens*, 0.083 for

C. crescentus, and 0.094 for *D. shibae*; p-value < 0.001 in permutation tests for all three

genomes) (**Figure 2**). These comparisons show that co-evolving genes that encode well-

characterized proteins (defined as present in the STRING and COG databases) and a subset of

genes needed for specific environmental conditions (as determined by the Fitness Browser

database) indeed tend to encode functionally related proteins. For example, *P. inhibens'* gene

pairs with the two largest Pearson's coefficients encode proteins that are involved in the same

biological processes (**Figure 3**): *imuB* and *dnaE2* genes (Pearson's coefficient r = 0.800) are

located in the same operon and are involved in SOS-induced mutagenesis and translesion

synthesis (47, 48), while *addA* and *addB* genes (Pearson's r = 0.735) are known to assemble into

the heterodimeric complex to facilitate homologous recombination and DNA repair (49, 50).

It is worth noting that some of the genes identified as co-evolving in our analysis are not

designated as encoding interacting proteins in the STRING database. However, given

incompleteness of our knowledge about functionality of proteins encoded in a bacterial genome,

these genes may represent functional connections yet unidentified in STRING. Indeed, ERC

analysis has been used to uncover novel protein-protein interactions, especially between

hypothetical proteins (40, 51, 52). Here are two examples of proteins identified as co-evolving in

our analyses and likely interacting based on what's known about their functions, but not

designated as such in the STRING database. The *yfgC* gene, which encodes a periplasmic

metalloprotease involved in assembly of outer membrane proteins (53), co-evolves with both the

lptD and *bamB* genes (**Figure 4**). The YfgC protein plays a crucial role in the assembly of LptD,

an outer membrane protein that participates in the lipopolysaccharide assembly ([53](#)). The YfgC

also interacts with the β-barrel-assembly machinery (BAM) complex, which consists of four

lipoproteins, including BamB, and facilitates the assembly and integration of proteins into the

outer membrane ([53](#), [54](#)).

GTA genes co-evolve with at least fifty-nine other gene families

By analyzing 1,470 gene families almost universally present among the 293

representative GTA-containing alphaproteobacteria, we identified 59 gene families that co-

evolve with at least 5 reference GTA genes (**Table S1**) (see **Methods** for selection criteria).

Notably, four of the 59 gene families - encoding tail fiber protein (DUF2793),

competence proteins (comEC and comF), and DNA-protecting protein that facilitates

homologous recombination (dprA) (**Table 1**) - have already been shown to play important roles

in the RcGTA lifecycle ([23](#), [24](#), [29](#)). Because tail fiber proteins are a part of the RcGTA particle

and thus physically interact with other RcGTA proteins ([29](#)), DUF2793's co-evolution with other

structural GTA genes is expected. The protein products of the remaining three genes (ComEC,

ComF, and DprA) are required for the acquisition of DNA delivered by RcGTAs, and interact

physically only with DNA molecules ([23](#), [24](#)). This finding demonstrates that the ERC approach

indeed could predict genes functionally linked to the GTA lifecycle.

The remaining 55 gene families are involved in various functions (**Tables 1, 2** and **S1**).

While 32 of the 55 gene families (**Table 2**) offer exciting opportunities for future research into

GTA lifecycle, 23 gene families (**Table 1**) can be either directly linked to the GTA lifecycle by

being involved in DNA repair or are likely to be under similar selection pressure as GTA genes

due to shared ecological importance (stress response, biofilm formation, oxidative respiration,

and cofactor biosynthesis), as elaborated below.

Three of the 22 genes – *mutY* (encoding a glycosylase), *phrB* (encoding a DNA

photolyase), and *tatD* (encoding an exonuclease) – play roles in repair of DNA damage induced

by various oxidative agents and UV light ([55-57]). Glycosylase actively modulates homologous

recombination ([58]), which could be important for facilitating integration of GTA-derived genetic

material into the recipient's genome ([6], [9]). Photolyase and tatD exonuclease do not directly

participate in homologous recombination, but are involved in DNA repair process ([6], [55], [56]) and

thus are likely to be under the similar selection pressure as GTA genes.

Two genes (*mazG* and *ydiU*) identified in our screen are involved in stress response. The

product of the *mazG* gene modulates the programmed cell death in *Escherichia coli* and regulates

intracellular level of ppGpp, the universal 'alarmone', which was previously implicated in the

regulation of GTAs production ([20], [59]). The ppGpp molecule is involved in a cellular response

to a variety of stress conditions, including nutritional stress. The product of the *ydiU* gene

mediates UMPylation of bacterial chaperones, improving bacterial fitness under the stressful

environmental settings ([60]).

Thirteen genes identified in our analyses have relevance to biofilms. While these genes

are linked to the formation of biofilms, they are also involved in a range of other molecular

functions. The *hrpB* gene, which encodes ATP-dependent RNA helicase, has been shown to be

important for both biofilm formation and adhesion on surfaces ([61]). The *ccmA* gene, *cycH* gene,

and a gene from COG5387 family (*ATP12*) are involved in oxidative respiration, which

promotes bacterial survival in the biofilms ([62], [63]). Moreover, as a group, 59 co-evolving gene

families are enriched in three metabolic pathways relevant to biofilms: cofactor biosynthesis,

folate biosynthesis and sulfur relay system (hypergeometric test, p-value < 0.05, Bonferroni

correction) (**Table 1**). Two genes from the 'cofactor biosynthesis' pathway (*moeA* and *moaC*) are

involved in the molybdenum cofactor biosynthesis. Both metabolism of folate and molybdenum

cofactors are important for biofilm formation ([64](#), [65](#)). The sulfur relay pathway is involved in

the tRNA modifications ([66](#)), which are implicated in fitness of bacteria within a biofilm ([62](#)).

Notably, five additional genes that encode tRNA modification enzymes (*mnmE*, *tilS*, *SUA5*,

dusA, *tadA*) are inferred to co-evolve with GTA genes (**Table 1**). Finally, the *tadB* gene is

involved in the assembly of the tad pili, which have been shown to be involved in promoting the

surface colonization and biofilm cohesion ([67](#), [68](#)). Interestingly, in *D. shibae tad* genes are co-

regulated with GTA genes, further corroborating linkage between tad pili and GTAs ([33](#)).

Discussion

By showing that GTA head-tail cluster genes, and especially genes within the same

functional module of the cluster, tend to co-evolve with each other, and by examining function-

coevolution relationship among proteins encoded in a model marine bacterium, we demonstrated

that the ERC method is an effective approach to uncover functional relationships among protein-

coding genes in bacteria, extending the method's applicability beyond eukaryotes. Applying the

method to GTA-encoding alphaproteobacterial genomes that span >700 million years of

evolution ([13](#)), we detected a significant evolutionary rate covariation of GTA head-tail cluster

genes with 59 protein-coding genes. Multiple genes in this dataset are involved in stress

response, DNA repair, homologous recombination, and biofilm formation. These functions are

consistent with the accumulating experimental and computational evidence about GTA

production, regulation and function in *R. capsulatus* and *C. crescentus*, and with previous

hypotheses and models of GTA production triggered under environmental stress ([6], [20]), GTAs

being involved in DNA repair in recipient cell ([6], [69]), and, most recently, of GTA production

occurring in biofilms ([36]). Our discovery that 13 biofilm-implicated genes co-evolve with GTA

genes further highlight the potential importance of biofilm settings for GTA production.

Alphaproteobacteria in general, and GTA-producing *R. capsulatus* and *C. crescentus* in

particular, are known to form biofilms ([36], [70-72]). Biofilms provide a microbial community with

benefits that cannot be achieved by the individual cells, such as protection against antibiotics

([73]) and viral infections ([74], [75]). Despite either shown or hypothesized benefits of GTA-

disseminated DNA to the recipient cells ([2], [6], [76]), zero relative fitness of the lysed GTA-

producing cells implies that the trait of encoding GTAs can only be favored by selection when

the benefits of receiving GTAs are confined to either clonal or very closely related cells that also

possess the genes encoding the suicidal GTA production trait. Encoding genes for synthesis of

specific polysaccharide receptors, which facilitate the adsorption of GTAs ([22]) and co-regulating

the receptor production in one fraction of a population with GTA production in another fraction

of a population, can limit GTAs' targets only to clonal cells or very closely related species.

Additionally, success of homologous recombination declines exponentially with the increase in

genomic sequence divergence ([77], [78]), further restricting the usefulness of GTA particles for

DNA repair to closely related cells.

Within such groups of closely related cells, GTAs can be viewed as "population-level

goods". However, any population-level goods system faces an inevitable rise of cheaters ([79]),

and a population of GTA producers would be susceptible to cheaters that would not produce GTA

particles but still have surface polysaccharides that serve as GTA receptors. Consistent with these

conjectures, we observe both the pseudogenization and complete loss of GTA systems in

multiple alphaproteobacterial lineages ([11], [13], [19]). Pseudogenized GTA gene clusters may

represent recently emerged cheater lineages, while the absence of GTA gene clusters could be a

result of cheater takeover in a species and consequent loss of GTA genes due to the deletion bias

([80]). (It should be noted that, in both cases, the loss of GTA production in these lineages could

also be attributed to acquisition of alternative molecular mechanisms to cope with nutritional

stress and DNA repair, or inhabiting niches where GTA production costs outweigh its benefits.)

Mathematical modeling showed that maintenance of GTA production trait can be difficult in

mixed populations of GTA producers and cheaters, at least under some conditions ([81]). Yet,

despite the likely appearance of cheaters and an observation of recurrent GTA loss in multiple

lineages, the GTA production trait has been persisting in alphaproteobacteria for hundreds of

millions of years ([13]), suggesting that some kind of population-level selection is successful.

However, details of how such selection operates remain unknown.

One possible solution for an "altruistic" trait to persist in a population over time is to

have the population segregated into small sub-populations, an evolutionary scenario first

modeled by Wilson ([82]) and subsequently shown to be equivalent to multi-level selection models

that emphasize close relatedness of sub-population members ([83], [84]). Under this model, the

cheaters arise stochastically and therefore are found in many but not all sub-populations.

Notably, sub-populations without cheaters outcompete sub-populations with cheaters by having

overall higher total productivity due to benefits of the population-level goods produced by the

altruistic trait. We hypothesize that GTA systems persist over time because GTA production

occurs in such spatially structured populations. We further hypothesize that *it is biofilms* that

facilitate the division of GTA-producing populations into isolated sub-populations. A biofilm

would ensure that clonal or closely related cells are in spatial proximity, plus they would protect

the GTA-producing sub-population from being invaded by other cells, including cheaters. Dense

packing of cells would also ensure that the released GTA particles are not dispersed in the

environment and reach their recipients (36). Biofilms would also trap the organic debris of the

lysed GTA-producer cells within the biofilm (85). DNA of these lysed cells could be used as a

part of a biofilm matrix (85), enhancing the sub-population isolation and protection from

environmental hazards (86). Other environmental and cellular debris could increase localized

nutrient availability. Previous experimental work on biofilms supports some of our conjectures.

In the GTA-producing *Caulobacter crescentus* the biofilm structure promotes clonal cells to

reside in proximity (71). Biofilm formation is also increased during the ecological competition,

providing microbes with the protection to resist invasion by different strains (87).

Building on the current knowledge and previous models of GTA evolution and function,

we propose the following model of selection acting on a structured, biofilm-forming bacterial

population and maintaining GTA production (**Figure 5**). When a population experiences

starvation, nutritional stress increases the generation of reactive oxygen species, which induces

DNA damage (88). In a structured population, the fate of each sub-population (i.e., of individual

biofilms) depends on the genetic make-up of its cells. In a sub-population of GTA producers

(GTA$^+$ cells), a small fraction of cells is "sacrificed", and their DNA is delivered to the

remaining cells or hoarded as part of the biofilm matrix, while the cellular debris are utilized as

additional nutrients. The resources are protected from invaders by the biofilm structure. As a

result, the sub-population counteracts the negative effects of nutrient scarcity and DNA damage,

and thus experiences, at worst, only a small population decline due to the lysed GTA$^+$ cells.

However, if cheaters arise within the biofilm boundaries, the composition of such sub-population

under multiple episodes of nutritional stress will change to a higher fraction of GTA non-

producers (GTA⁻ cells), as these types of cells will not be lost due to lysis during GTA production

and yet will experience all benefits of the population-level goods released by GTA⁺ cells.

Eventually, the sub-population will lose GTA production trait. In a sub-population of GTA⁻ cells,

mutational load due to DNA damage and limited nutrients will result in a decline of the sub-

population size. Therefore, GTA⁺ sub-populations will have higher relative fitness in comparison

to GTA⁻ sub-populations, resulting in the larger overall number of GTA⁺ cells in the combined

population. Thus, the GTA production trait will be maintained in the population as a whole.

Although bits of experimental evidence used in the above model come mostly from the

research on GTAs in *Rhodobacter capsulatus* and *Caulobacter crescentus*, we hypothesize that

our model is applicable to other GTA-containing alphaproteobacterial species, because the

detected co-evolution patterns span multiple diverse alphaproteobacterial clades.

Materials and Methods

Identification of 293 representative alphaproteobacterial genomes with GTA regions

Initially, 1,642 alphaproteobacterial genomes and annotations of their protein-coding

genes were retrieved from the NCBI's Assembly and RefSeq database (accessed June 2022) ([89])

(**Table S2**). In these genomes, GTA regions were predicted using GTA-Hunter program with

default parameters ([19]). Because GTA-Hunter looks only for 11 out of the 17 genes of the

RcGTA's head-tail cluster, the remaining GTA genes were identified via BLASTP searches (E-

value < 0.1) ([90]), using as queries the curated set of GTA regions from ([19]). Only BLASTP

matches that are located within the GTA-Hunter-predicted GTA regions were added. Using this

procedure, GTA regions were identified in 701 genomes.

To avoid presence of multiple highly similar GTA regions in downstream analyses, the

701 genomes were clustered into 392 Operational Taxonomic Units (OTUs) using the <u>A</u>verage

<u>N</u>ucleotide <u>I</u>dentity (ANI) cutoff of 95%, calculated via fastANI v1.1 (91). Within each OTU,

GTA regions were examined for "completeness", defined as having 14 out of the 17 head-tail

cluster genes (genes *g1*, *g3.5* and *g7* were excluded because they are not easily detected across

GTA-contaning alphaproteobacterial clades (13)). Incomplete GTA regions were discarded. This

criterion reduced the number of OTUs to 293. Within each of the 293 OTUs, only one, randomly

selected, genome and its GTA region were retained for subsequent analyses (**Table S3**).

Reconstruction of the reference phylogenomic tree

From the set of 120 marker genes widely used for phylogenomic taxonomy (92), 84 gene

families were detected in a single copy in at least 95% of the 293 genomes using AMPHORA2

(93). Amino acid sequences of each of these 84 gene families were aligned using MAFFT v7.505

with the 'linsi' option (94). The alignments were concatenated, and the best substitution model

for each alignment and the optimal partition scheme were established via ModelFinder (95). The

maximum-likelihood phylogeny was reconstructed using IQ-TREE v2.2 (96). The tree was

rooted using the *Emcibacterales* and *Sphingomonadales* taxonomic orders, using the previously

observed branching order of the *Alphaproteobacteria* as a guide (13, 19).

Selection of Reference GTA genes

The amino acid sequences of the 14 GTA genes from the GTA regions of the 293

genomes were retrieved and aligned using MAFFT v7.505 with the 'linsi' option. Phylogenetic

trees were reconstructed from each alignment using IQ-TREE v2.2 (96) under the best

substitution model identified by ModelFinder ([95]). Each tree was compared to the reference tree

using the normalized quartet scores calculated in ASTRAL v5.7.8 ([97]). Eleven GTA genes that

exhibited a high congruency with the reference phylogeny (quartet score > 0.8) (**Figure S2**) were

designated as "reference GTA genes" and are referred as such throughout the manuscript.

Identification and functional annotation of gene families in 293 GTA-containing genomes

Gene families were defined as orthologous groups identified in Broccoli v1.2 ([98]), using

DIAMOND ([99]) for protein similarity searches and the maximum-likelihood method for

phylogenetic reconstructions. Gene families that are present in a single copy in at least 50% of

the 293 GTA-containing genomes (1,470 in total) were retained for further analyses.

To assign COG functional annotations to the gene families, one randomly selected

representative from each family was used as a query against the eggNOG database v5.0.2 and

processed through eggNOG-mapper v2.1.9 workflow ([100]). For gene families found to be co-

evolving with the GTA region (see below), additional annotations were sought out using

PaperBLAST (accessed in December 2022) ([101]) and CD-searches against CDD database v3.20

(accessed in December 2022) ([102]).

Inference of evolutionary rate covariation

Amino acid sequences of each gene family and each reference GTA gene were aligned

using MAFFT v.7.505 with the 'linsi' option ([94]) . For gene families that are not found in all 293

genomes, the absent taxa were pruned from the reference tree using functions from the *ete3*

package ([103]). For each gene set, the topology of taxa relationships was constrained to the

reference phylogeny and branch lengths were estimated via IQ-TREE v2.2 ([96]), using the best

substitution model suggested by ModelFinder ([95]). The trees were rooted using relationships in

the reference phylogeny as a guide.

Covariations of evolutionary rates among 1,470 gene families and 11 GTA reference

genes were examined rates using the CovER pipeline, as implemented in PhyKIT v1.11.12 ([38],

[104]). Within the pipeline, the following steps were carried out. For each pair, their trees were

pruned to retain only shared taxa. All trees were corrected for the differences in mutation rates

and divergence times among taxa; this was accomplished by dividing the length of each branch

by the length of the corresponding branch of the reference tree. Branches with the normalized

length > 5 were removed from further analyses, and the retained branch lengths were Z-

transformed. For every pair, Pearson correlation coefficient was calculated. A pair of genes was

designated as co-evolving, if the Pearson correlation coefficient was positive and had p-value <

0.05 after Bonferroni correction for multiple testing.

The above-described co-variation analysis was carried out on five datasets: among 11

GTA reference genes (11 x 10/2 = 55 comparisons), between GTA genes and 1,470 gene families

(11 x 1,470 = 16,170 comparisons), among 1,320 gene families present in GTA-containing

genome *Phaeobacter inhibens* (1,320 x 1,319/2 = 870,540 comparisons), among 1,199 gene

families present in GTA-producing genome *Caulobacter crescentus* (1,199 x 1,198/2 = 718,201

comparisons), and among 1,255 detected in GTA-producing genome *Dinoroseobacter shibae*

(1,255 x 1,254 = 786,885). The *P. inhibens, C. crescentus and D.shibae* analyses resulted in

10,514, 9,373 and 9,675 co-evolving gene pairs, respectively (**Figure S1**). The gene pairs

information was assembled into co-evolution networks, in which nodes represent gene families

and edges depict co-evolution relationships. To annotate nodes in the co-evolution networks with

functional categories, the sub-networks of 1,040 out of 1,320 gene families (for *P. inhibens*), 953

out of 1,199 gene families (for *C. crescentus*), and 997 out of 1,255 gene families (for *D. shibae*),

that had unambiguous COG assignments were extracted. The COG functional annotations of

genes were assigned as labels.

To minimize the number of false positives and to shorten the list of candidate gene

families that co-evolve with GTA genes, the following criteria were applied in addition to

Pearson's R > 0 and Bonferroni-corrected p-value < 0.05: A gene family was required (i) to co-

evolve with at least 5 GTA reference genes and (ii) to be above the 95th percentile in the of 1,470

gene families ranked by both p-value and Pearson's R for at least 5 GTA reference genes. Under

these criteria, 59 gene families were retained for further analyses.

Reconstruction of protein-protein interaction networks

Amino acid sequences of the 1,320 (*P. inhibens*), 1,199 (*C. crescentus*), and 1,255 (*D.*

shibae) above-described gene families were used as queries against the STRING database v.11.5

([45](#)), with the high confidence score cutoff and all available sources. This search resulted in

8,612, 8,385, and 8,366 interacting protein-protein pairs for *P. inhibens*, *C. crescentus*, and *D.*

shibae, respectively. The information was assembled into a *Phaeobacter inhibens* protein-protein

interactions (PPI) networks, in which nodes represent genes and edges depict PPIs.

Reconstruction of co-fitness networks

P. inhibens', *C. crescentus'*, and *D. shibae*'s gene pairs with similar fitnesses across a

wide range of different experimental conditions were retrieved from the Fitness Browser ([46](#))

(accessed October 2023). Gene pairs were designated as co-fit if they either had a co-fitness

value > 0.75, or they had a co-fitness value > 0.60 and were conserved in other bacterial species

(46). This search resulted in 569, 2,657, and 540 co-fit gene pairs for *P. inhibens*, *C. crescentus*,

and *D. shibae*, respectively. The information was assembled into co-fitness networks, in which

nodes represent genes and edges depict co-fitness associations.

Comparison of networks and identification of subnetworks

The similarity between *P. inhibens' C. crescentus'*, and *D. shibae'* co-evolution networks

and either PPI or co-fitness networks was assessed by calculating Jaccard index (105), which

measures the fraction of edges shared between the networks. The null distribution of Jaccard

indices was created by randomly re-shuffling of the evolutionary rate covariation network 1,000

times.

Tendency of nodes from the same COG category to connect with each other was

measured by an assortativity coefficient calculated for the co-evolution subnetworks with

unambiguous COG assignments. The coefficient quantifies the connectivity of nodes belonging

to the same class and varies between 1 (only nodes of the same class are connected) and -1 (only

nodes that belong to different classes are connected). To assess the significance of the observed

assortativity values, the permutation test was performed by random shuffling of COG labels

1,000 times. The values of assortativity coefficients were calculated using *igraph* v1.3.5 (106).

All networks were visualized using *igraph* v1.3.5 (106).

KEGG pathways enrichment analysis for 59 genes that co-evolve with GTAs

Each of the 59 gene families was assigned a KEGG Orhology (KO) label using

BlastKOALA (107). Significantly enriched pathways were identified by the hypergeometric test

(p-value < 0.05 with Bonferroni correction for multiple testing), as implemented in the

clusterProfiler package v4.4.4 ([108](#)).

Data Availability

The genomes used in this study are publicly available via NCBI Assembly

(https://www.ncbi.nlm.nih.gov/assembly) database. The accession numbers of these genomes are

listed in **Table S2**. The following datasets, which were derived from the genomes, are available

in the FigShare repository (https://doi.org/10.6084/m9.figshare.23929551.v1): multiple sequence

alignment of GTA genes; unconstrained and constrained phylogenetic trees of GTA genes;

concatenated alignment of phylogenomic markers and reconstructed reference phylogenomic

tree; amino acid sequences of 1,470 gene families; constrained phylogenetic trees of 1,470 gene

families; covariation of evolutionary rates for all performed pairwise gene comparisons;

Phaeobacter inhibens', *Caulobacter crescentus', Dinoroseobacter shibae'*s co-evolutionary

networks and their subnetworks of nodes with unambiguous GOG assignment, protein-protein

interaction networks, fitness networks, and lists of COG functional category assignments for

nodes.

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Tables

Table 1. Twenty-seven gene families that co-evolve with reference GTA genes and discussed throughout the manuscript.

Gene name	Representative GenBank accession number	Functional Annotation[@]	Number of genomes that encode the gene
DUF2793	ADE83936.1	tail fiber protein[1]	225
comEC	ADE86092.1	competence protein	280
comF	ADE83962.1	competence protein F	281
dprA	ADE86822.1	DNA-protecting protein DprA	288
phrB	ADE86685.1	deoxyribodipyrimidine photo-lyase	228
mutY	ADE83991.1	A/G-specific adenine glycosylase	290
tatD	ADE85006.1	TatD-related deoxyribonuclease family protein	291
mazG	ADE85524.1	MazG family protein	291
ydiU	ADE85462.1	protein of unknown function UPF0061	243
hrpB	ADE86856.1	ATP-dependent RNA helicase HrpB	276
ccmA	ADE85530.1	heme exporter protein A	293
cycH	ADE86047.1	cytochrome c-type biogenesis protein CycH	226
ATP12	ADE84099.1	ATP12 chaperone protein family	293
pdxA[*]	ADE86420.1	4-hydroxythreonine-4-phosphate dehydrogenase	290
coaE[*]	ADE83834.1	dephospho-CoA kinase	292
hemD[*]	ADE87233.1	uroporphyrinogen-III synthase	286
ribD[*]	ADE86804.1	riboflavin biosynthesis protein RibD	221
folk[*#]	ADE87043.1	2-amino-4-hydroxy-6-hydroxymethyldihydropteridine pyrophosphokinase	289
moeA[*#]	AAV95421.1	molybdenum cofactor biosynthesis protein A	270
moaC[*#$]	ADE86569.1	molybdenum cofactor biosynthesis protein C-2	280
moeB[$]	ADE84219.1	molybdenum cofactor biosynthesis protein B-1	282
mnmE	ADE83829.1	tRNA modification GTPase TrmE	289
tilS	QNR64972.1	tRNA lysidine(34) synthetase TilS	282
SUA5	ADE84169.1	Sua5/YciO/YrdC/YwlC family protein	292
dusA	ADE85522.1	tRNA-dihydrouridine synthase A	216
tadA	ADE86235.1	tRNA-specific adenosine deaminase	293
tadB	ADE84271.1	type II secretion system protein	207

[@]As provided in the GenBank records, except when a reference is provided
[*]Biosynthesis of cofactors (KEGG pathway ko01240)
[#]Folate biosynthesis (ko00790)
[$]Sulfur relay system (ko04122)
[1]Hynes AP et al. 2016. Functional and evolutionary characterization of a gene transfer agent's multilocus "genome". Mol Biol Evol 33:2530-2543.

1 **Table 2. Thirty-two gene families that co-evolve with reference GTA genes, but without**
2 **known connection to the GTA production cycle.**

Gene name	Representative GenBank accession No.	GenBank Functional Annotation	Number of genomes that encode the gene
prmC	QNR62505.1	peptide chain release factor N(5)-glutamine methyltransferase	292
bioC	ADE83961.1	conserved hypothetical protein	292
mhpC	ADE84522.1	hydrolase, alpha/beta fold family	289
miaA	ADE85369.1	tRNA delta(2)-isopentenylpyrophosphate transferase	291
-	ADE86839.1	protein-L-isoaspartate O-methyltransferase-2	292
phnP	ADE85005.1	metallo-beta-lactamase family protein	288
ispDF	ADE85540.1	bifunctional 2-C-methyl-D-erythritol 4-phosphate cytidylyltransferase/2-C-methyl-D-erythritol 2,4-cyclodiphosphate synthase	282
glmU	ADE85246.1	bifunctional UDP-N-acetylglucosamine diphosphorylase/glucosamine-1-phosphate N-acetyltransferase	288
yfgZ	ADE86835.1	glycine cleavage T protein-2	292
yhiN	ADE84019.1	HI0933-like protein	193
-	ADE87182.1	conserved hypothetical protein	243
pcnB	ADE83954.1	CCA-adding enzyme	291
yfiH	ADE86534.1	protein of unknown function DUF152	293
-	ADE86535.1	protein of unknown function DUF185	293
alr	ADE85319.1	alanine racemase	251
rspA	ADE86886.1	mandelate racemase/muconate lactonizing enzyme family protein	208
ppiD	ADE86084.1	peptidyl-prolyl cis-trans isomerase D	291
aroE	ADE83833.1	shikimate 5-dehydrogenase	291
glnE	ADE86144.1	glutamate-ammonia-ligase adenylyltransferase	285
rns	ADE84242.1	ribonuclease T2 family protein	260
gluQ	ADE85705.1	glutamyl-Q tRNA(Asp) synthetase	289
MA20_39615	ADE85459.1	protein of unknown function DUF985	201
ptpA	ADE86851.1	protein-tyrosine-phosphatase	172
rne	ADE85895.1	ribonuclease E	289
ptr1	ADE86148.1	oxidoreductase, short-chain dehydrogenase/reductase family	259
queG	ADE86491.1	4Fe-4S ferredoxin, iron-sulfur cluster binding protein	286

-	ADE84017.1	NAD-dependent epimerase/dehydratase family protein	279
nnrD	ADE85417.1	YjeF-related protein family	262
pepA	ADE86425.1	leucyl aminopeptidase-2	291
-	ADE84176.1	peptidase, S58 family	191
pepN	ADE84605.1	aminopeptidase N	269
MA20_18095	ADE84243.1	alcohol dehydrogenase, zinc-binding domain protein	262

Figures

Figure 1. Co-evolution of 11 reference GTA genes from head-tail clusters. (A) The head-tail

cluster of the RcGTA, as encoded in *R. capsulatus* strain SB 1003 genome (GenBank accession

CP001312.1; spanning locus tags RCAP_rcc01682 - RCAP_rcc01698). Each gene is represented

by an arrow and is drawn proportional to its length (see scale bar). Genes shown in non-gray

color correspond to the 11 GTA reference genes used in the ERC analysis. Reference genes from

each functional module are depicted in a distinct color. **(B)** Co-evolution network of the

reference GTA genes. Nodes represent genes and are connected by edges if there is a significant

evolutionary rate covariation (Pearson's R > 0 and p-value <0.05 after Bonferroni correction).

(C) Comparison of the rate covariation strength in reference GTA genes that belong either to

different functional modules ("Between Modules") or to the same functional module ("Within

Modules). Boxplots represent median values that are bounded by first and third quartiles.

1   Whiskers illustrate data points that lie within $1.5 *$ interquartile range. Significance was

2   measured using Mann-Whitney U-test.

Figure 2. Strengths of correlations between the covariation evolutionary rate of genes and function of the proteins the genes encode, as measured by permutation tests. The analyses were carried out for **(A)** *Phaeobacter inhibens*, **(B)** *Caulobacter crescentus*, and **(C)** *Dinoroseobacter shibae*. Graphs on the left show the comparisons between the co-evolution and PPI networks, while graphs in the middle show the comparisons between co-evolution and co-fitness network. For these graphs, the distributions in brown represent distances between the PPI/co-fitness networks and 1,000 co-evolution networks, in which edges were randomly shuffled. The dashed red lines indicate the Jaccard index from the non-shuffled network

1   comparisons. Graphs on the right show positive assortativity between co-evolution and COG

2   functional category assignment. The distributions in brown represent assortativity coefficient

3   values for 1,000 networks, in which COG labels were randomly shuffled. The dashed red lines

4   indicate the assortativity coefficient of the non-shuffled network.

Figure 3. Covariation of evolutionary rates for two gene pairs in *P. inhibens* with the largest

Pearson's coefficients. Each dot represents the normalized branch length of the proteins shown

on x- and y-axes. Blue line depicts the linear regression line. The value of Pearson's R is shown

on each panel.

Figure 4. Covariation of evolutionary rates for two gene pairs in *P. inhibens* with no

evidence of interactions for their protein products in the STRING database. Each dot

represents the normalized branch length of the proteins shown on x- and y-axes. Blue line depicts

the linear regression line. The value of Pearson's R is shown on each panel.

3   **Figure 5. The proposed model of between-group selection that preserves the trait of GTA**

4   **production in a bacterial population of closely related cells.** See **Discussion** section for

5   detailed description.