Metabolic differentiation of co-occurring Accumulibacter clades revealed through genome-resolved metatranscriptomics

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ABSTRACT

Natural microbial communities consist of closely related taxa that may exhibit phenotypic differences and inhabit distinct niches. However, connecting genetic diversity to ecological properties remains a challenge in microbial ecology due to the lack of pure cultures across the microbial tree of life. *'Candidatus* Accumulibacter phosphatis' is a polyphosphate-accumulating organism that contributes to the Enhanced Biological Phosphorus Removal (EBPR) biotechnological process for removing excess phosphorus from wastewater and preventing eutrophication from downstream receiving waters. Distinct Accumulibacter clades often co-exist in full-scale wastewater treatment plants and lab-scale enrichment bioreactors, and have been hypothesized to inhabit distinct ecological niches. However, since individual strains of the Accumulibacter lineage have not been isolated in pure culture to date, these predictions have been made solely on genome-based comparisons and enrichments with varying strain composition. Here, we used genome-resolved metagenomics and metatranscriptomics to explore the activity of co-existing Accumulibacter strains in an engineered bioreactor environment. We obtained four high-quality genomes of Accumulibacter strains that were present in the bioreactor ecosystem, one of which is a completely contiguous draft genome scaffolded with long Nanopore reads. We identified core and accessory genes to investigate how gene expression patterns differed among the dominating strains. Using this approach, we were able to identify putative pathways and functions that may confer distinct functions to Accumulibacter strains and provide key functional insights into this biotechnologically significant microbial lineage.

IMPORTANCE

'*Candidatus* Accumulibacter phosphatis' is a model polyphosphate accumulating

organism that has been studied using genome-resolved metagenomics,

metatranscriptomics, and metaproteomics to understand the EBPR process. Within the

Accumulibacter lineage, several similar but diverging clades are defined by shared

sequence identity of the polyphosphate kinase (*ppk1)* locus. These clades are predicted

to have key functional differences in acetate uptake rates, phage defense mechanisms,

and nitrogen cycling capabilities. However, such hypotheses have largely been made

based on gene-content comparisons of sequenced Accumulibacter genomes, some of

which were obtained from different systems. Here, we performed time-series genome-

resolved metatranscriptomics to explore gene expression patterns of co-existing

Accumulibacter clades in the same bioreactor ecosystem. Our work provides an approach

for elucidating ecologically relevant functions based on gene expression patterns

between closely related microbial populations.

INTRODUCTION

Naturally occurring microbial assemblages are composed of closely related species or subpopulations and harbor extensive genetic diversity. Coherent lineages are often comprised of distinct clades, ecotypes, or "backbone subpopulations" defined by high within-group sequence similarities that translate to ecologically relevant diversity (1–3). For example, genetically diverse ecotypes of the marine cyanobacterium *Prochlorococcus* that are 97% identical by their 16S ribosomal RNA gene sequences exhibit markedly different light-dependent physiologies and distinct seasonal and geographical patterns (1, 2, 4, 5). Closely related *Nitrospira* representing species-like lineages that coexisted for long periods of time in a full-scale wastewater treatment plant exhibited functional differences in preferences for nitrite concentrations and carbon substrates (6). However, dissecting the emergent ecological properties of species-like coherent microbial lineages is still a grand challenge in microbial ecology given that these principles are likely not universal among the breadth of microbial diversity, and is further hindered when there is a lack of pure cultures (7–9).

Enhanced Biological Phosphorus Removal (EBPR) is an economically and environmentally significant process for removing excess phosphorus from wastewater. This process depends on polyphosphate accumulating organisms (PAOs) that polymerize inorganic phosphate into intracellular polyphosphate. '*Candidatus* Accumulibacter phosphatis' (hereafter referred to as Accumulibacter) is a member of the *Betaproteobacteria* in the *Rhodocyclaceae* family and has long been a model PAO (10, 11). Accumulibacter achieves net phosphorus removal through cyclical anaerobic-aerobic phases of feast and famine. In the initial anaerobic phase, abundantly available volatile

fatty acids (VFAs) such as acetate are converted to polyhydroxyalkanoates (PHAs), a

carbon storage polymer. However, PHA formation requires significant ATP input and

reducing power, which is supplied through polyphosphate and glycogen degradation. In

the subsequent aerobic phase in which oxygen is available as a terminal electron

acceptor and soluble carbon sources are depleted, Accumulibacter uses PHA reserves

for growth. Accumulibacter recovers energy during aerobic PHA degradation by

replenishing polyphosphate and glycogen reserves, which can be later used for future

PHA formation as the anaerobic/aerobic cycle repeats. This feast-famine oscillation

through sequential anaerobic-aerobic cycles operating on minute-to-hourly time scales

gives rise to net phosphorus removal and the overall EBPR process (10, 12). A few

'omics-based studies have revealed potential regulatory modules that could coordinate

Accumulibacter's complex physiological behavior during these very dynamic

environmental conditions (13–16), but few have attempted to assign unique gene

expression dynamics to specific clades (17).

Accumulibacter can be subdivided into two main types (I and II) and further

subdivided into multiple clades based upon polyphosphate kinase (*ppk1*) sequence

identity since the 16S rRNA marker is too highly conserved among the breadth of known

Accumulibacter lineages to resolve species-level differentiation (18–21). The two main

types share approximately 85% nucleotide identity across the *ppk1* locus (21) which

mirrors genome-wide average nucleotide identity (ANI) (22). The persistence of several

phylogenetically distinct clades within the Accumulibacter lineage in both full-scale

wastewater treatment plants and lab-scale enrichment bioreactors suggests that different

clades may inhabit distinct ecological niches (17, 23). This is largely supported by

comparative genomics of Accumulibacter metagenome-assembled genomes (MAGs)

recovered from different bioreactor systems and classified using the *ppk1* locus (14, 17,

22, 24–27). Members of different clades have been hypothesized to vary in their acetate

uptake rates, nitrate reduction capacity, and phage defense mechanisms (22, 26). For

example, clade IA seems to exhibit higher acetate uptake rates and phosphate release

rates, whereas evidence exists that clade IIA can reduce nitrate but clade IA cannot (25,

28). However, the full breadth of ecological differentiation among Accumulibacter clades

is not yet clear.

Here, we used genome-resolved metagenomics and time-series

metatranscriptomics to investigate gene expression patterns of co-existing

Accumulibacter strains (representing two main clades) during a standard EBPR cycle.

We assembled four high-quality genomes of the dominant (clades IA and IIC) and low

abundant (clades IIA and IIF) Accumulibacter strains present in the bioreactor ecosystem.

Additionally, we constructed a contiguous draft genome of an Accumulibacter clade IIC

genome achieved using long Oxford Nanopore Technology (ONT) reads, representing

one of the highest-quality genomes for this clade recovered to date. Using these

assembled genomes, we performed time-series RNA-sequencing throughout a typical

EBPR feast-famine cycle to study expression profiles of different Accumulibacter strains,

with an emphasis on core and flexible gene content. More generally, our work reveals

putative ecological functions of co-existing taxa within a dynamic ecosystem.

MATERIALS AND METHODS

Bioreactor Operation and Sample Collection

A laboratory-scale sequence batch reactor (SBR) was seeded with activated sludge from the Nine Springs Wastewater Treatment Plant (Madison WI, USA) during August 2015. The bioreactor was operated to simulate EBPR as described previously (24). Briefly, an SBR with a 2-L working volume was operated with the established biphasic feast-famine conditions: a 6-h cycle consisted of the anaerobic phase (sparging with N_2 gas), 110-min; aerobic (sparging with oxygen), 180-min; settle, 30-min; draw and feed with an acetate-containing synthetic wastewater feed solution, 40-min. A reactor hydraulic residence time of 12-h was maintained by withdrawing 50% of the reactor contents after the settling phase, then filling the reactor with fresh nutrient feed; a mean solids retention time of 4-d was maintained by withdrawing 25% of the mixed reactor contents each day immediately prior to a settling phase. Allylthiourea was added to the synthetic feed solution to inhibit ammonia oxidation and indirectly inhibit nitrification/denitrification.

Three biomass samples for metagenomic sequencing were collected in September of 2015 by centrifuging 2-mL of mixed liquor at 8,000 x g for 2 min, and DNA was extracted using a phenol:chloroform extraction protocol. Seven samples for RNA sequencing were collected throughout a single EBPR cycle (3 in the anaerobic phase, 4 in the aerobic phase) in October of 2016 following the sampling strategy conducted by Oyserman et al. (13). Samples were flash-frozen on liquid nitrogen immediately after centrifuging and discarding the supernatant. RNA was extracted using a TRIzol-based extraction method (Thermo Fisher Scientific, Waltham, MA) followed by phenol-

chloroform separation and RNA precipitation. RNA was purified following an on-column

DNAse digestion using the RNase-Free DNase Set (Qiagen, Venlo, Netherlands) and

cleaned up with the RNeasy Mini Kit (Qiagen, Venlo, Netherlands). Accumulibacter clade

quantification was performed on biomass samples collected on the same day of the

metatranscriptomics experiment using clade-specific *ppk1* qPCR primers as described by

Camejo et al. (23).

Metagenomic and Metatranscriptomic Library Construction and Sequencing

Metagenomic libraries were prepared by shearing 100 ng of DNA to 550 bp long

products using the Covaris LE220 (Covaris) and size selected with SPRI beads (Beckman

Coulter). The fragments were ligated with end repair, A-tailing, Illumina compatible

adapters (IDT Inc) using the KAPA-Illumina library preparation kit (KAPA Biosystems).

Libraries were quantified using the KAPA Biosystem next-generation sequencing library

qPCR kit and ran on a Roche LightCycler 480 real-time PCR instrument. The quantified

libraries were prepared for sequencing on the Illumina HiSeq platform using the v4

TruSeq paired-end cluster kit and the Illumina cBot instrument to create a clustered flow

cell for sequencing. Shotgun sequencing was performed at the University of Wisconsin –

Madison Biotechnology Center DNA Sequencing facility on the Illumina HiSeq 2500

platform with the TruSeq SBS sequencing kits, followed by 2x150 indexing. Raw

metagenomic data consisted of 219.4 million 300-bp Illumina HiSeq reads with

approximately 3.9 Gbp per sample. Nanopore sequencing was performed according to

the user's manual version SQK-LSK108.

Total RNA submitted to the University of Wisconsin-Madison Biotechnology Center

was verified for purity and integrity using a NanoDrop 2000 Spectrophotometer and an

Agilent 2100 BioAnalyzer, respectively. RNA-Seq paired-end libraries were prepared

using the TruSeq RNA Library Prep Kit v2 (Illumina, San Diego, CA). Each sample was

processed for ribosomal depletion, using the Ribo-Zero™ rRNA Removal Kit (Bacteria).

mRNA was purified from total RNA using paramagnetic beads (Agencourt RNAClean XP

Beads, Beckman Coulter Inc., Brea, CA) and fragmented by heating in the presence of a

divalent cation. The fragmented RNA was then converted to cDNA with reverse

transcriptase using SuperScript II Reverse Transcriptase (Invitrogen, Carlsbad,

California, USA) with random hexamer priming and the resultant double-stranded cDNA

was purified. cDNA ends were repaired, adenylated at the 3' ends, and then ligated to

Illumina adapter sequences. The quality and quantity of the DNA were assessed using

an Agilent DNA 1000 series chip assay and Thermo Fisher Qubit dsDNA HS Assay Kit.

Libraries were diluted to 2nM, pooled in an equimolar ratio, and sequenced on an Illumina

HiSeq 2500, using a single lane of paired-end, 100 bp sequencing, and v2 Rapid SBS

chemistry.

Metagenomic Assembly and Annotation

We applied two different assembly and binning approaches to obtain high-quality

genomes of the dominant Accumulibacter strains present in the reactors. For the first

approach, Illumina unmerged reads were quality filtered and trimmed using the Sickle

software v1.33 (29). Reads were merged with FLASH v1.0.3 22 (30), with a mismatch

value of ≤0.25 and a minimum of ten overlapping bases from paired sequences, resulting

in merged read lengths of 150 to 290 bp. FASTQ files were then converted to FASTA

format using the Seqtk software v1.0 (31). Metagenomic reads from all three samples

were then co-assembled using the Velvet assembler with a k-mer size of 65 bp, a

minimum contig length of 200 bp, and a paired-end insert size of 300 bp (32). Metavelvet

was used to improve the assembly generated by Velvet (33). Metagenomic contigs were

then binned using Maxbin (34). This approach allowed us to assemble high-quality

genomes of clades IIA and IIC, named UW5 and UW6, respectively. Long Nanopore

reads were generated under the standard protocol and used to scaffold assembled

contigs with MeDuSa (35), and manually inspected to remove short contigs and

decontaminated using ProDeGe (36) and Anvi'o (37). Further scaffolding was performed

on both of these genomes using Nanopore long reads using LINKS (38) and GapCloser

(39).

Because this pipeline did not produce high-quality genomes of clades IA and IIF,

we applied a different approach to assemble these genomes. All reads from each

metagenomic sample were individually and co-assembled assembled using metaSPAdes

(40). Reads from each metagenome were mapped against each of the assemblies using

bbmap with a 95% sequence identity cutoff to obtain differential coverage (41), and

contigs were binned using MetaBat (42). Identical clusters of bins were dereplicated

across assemblies using dRep (43) to obtain the best quality genome of both clades IA

and IIF, named UW4 and UW7, respectively. All genomes were quality checked using

CheckM (44) and functional annotations assigned with Prokka and KofamKOALA (45,

46). We were unable to scaffold the genomes of UW4-IA and UW7-IIF with long Nanopore

reads because of their low abundance at the time of metagenomic sequencing.

Each genome was assigned to a particular clade both by comparing the *ppk1*

sequence identity and ANI to previously published Accumulibacter genomes. A *ppk1*

database was created using sequences from previously published Accumulibacter

references and clone sequences. We searched for the *ppk1* gene in our draft genomes

using this database and aligned the corresponding hits with MAFFT (47). A phylogenetic

tree of aligned *ppk1* gene sequences from Accumulibacter references, select clone

sequences, and the outgroups *Dechloromonas aromatica RCB* and *Rhodoc*yclus *tenuis*

DSM 110 with RAxML v8.1 with 100 rapid bootstraps (48). To use any given

Accumulibacter reference genome in downstream comparisons, a confident *ppk1* hit had

to be identified using the above methods. As a technical note, the IA-UW2 strain

assembled by Flowers et al. (22) was renamed to UW3, as the original assembly

contained an additional contig that was likely from a prophage. The prophage contig was

removed from the IA-UW2 strain and renamed to UW3, and therefore the UW numerical

nomenclature follows in sequential order after UW3. A phylogenetic tree of *ppk1*

nucleotide sequences was performed and compared to select clone sequences. Pairwise

genome-wide ANI was calculated between the four Accumulibacter draft genomes and

all available Accumulibacter genomes in Genbank with FastANI (49). A species tree of all

Accumulibacter references and outgroup genomes was constructed using single-copy

markers from the GTDBK-tk (50), aligned with MAFFT (47), built with RAxML with 100

rapid bootstraps (48), and visualized in iTOL (51). To compare genome-wide ANI scores

of Accumulibacter references with pairwise nucleotide identity of the *ppk1* locus of all

references, we performed pairwise BLAST for all *ppk1* coding regions and reported the

percent identity (52).

Identification of Core and Accessory Gene Content

We identified core and accessory gene content of Accumulibacter clades through

clustering orthologous groups of genes (COGs) using PyParanoid (53). We used the four

Accumulibacter MAGs generated in this study (Table 1) and high-quality Accumulibacter

reference genomes (above 90% completeness and less than 5% redundancy) for this

analysis, with *Dechloromonas aromatica RCB* and *Rhodocyclus tenuis DSM 110* as

outgroups (Accumulibacter references listed in Supplementary Table 1 available at

https://figshare.com/articles/dataset/Accumulibacter_References_Metadata/13237148).

Briefly, an all-vs-all comparison of proteins for all genomes was performed using

DIAMOND (54), pairwise homology scores calculated with the InParanoid algorithm (55),

gene families constructed with MCL (56), and HMMs built for each gene family with

HMMER (57). A phylogenetic tree was constructed for genomes used for the COGs

analysis by using the coding regions of the *ppk1* locus and overlaid with the

presence/absence of core and flexible gene content using the ete3 python package (58).

A similarity score between UW Accumulibacter genomes was calculated as the pairwise

Pearson correlation coefficient between gene families using the numpy python package

(59). The presence and absence of different gene families were visualized in an upset

plot between UW Accumulibacter genomes using the ComplexUpset package based on

the UpSetR package in R (60). All data wrangling and plotting were performed using the

tidyverse suite of packages in R (61).

Metatranscriptomics Mapping and Processing

Metatranscriptomics reads from each of the seven samples were quality filtered

using fastp (62) and rRNA removed with SortMeRNA (63). The coding regions of all four

Accumulibacter genomes assembled in this study (Table 1) were predicted with Prodigal

(64) and annotated with both Prokka and KofamKOALA (45, 46), and concatenated

together to create a mapping index. Metatranscriptomic reads were competitively

pseudoaligned to the reference index and counts quantified with kallisto (65). Genes with

a sum of more than 10,000 counts across all 7 samples were removed, as these are likely

ribosomal RNAs that were not removed previously. Additionally, genes annotated as

rRNAs by barrnap were manually removed (45).

To explore genes and metabolic functions that may exhibit hallmark anaerobic-

aerobic feast-famine cycling patterns among the dominant IA-UW4 and IIC-UW6 strains,

we identified sets of genes that were differentially expressed between anaerobic and

aerobic conditions using DESeq2 (66). Differential gene expression calculations were

performed for each strain separately to account for differences in the relative abundance

of metatranscriptomic reads mapping back to each of the four MAGs. Low-count genes

were removed individually for each genome by requiring that all genes had to have more

than 10 counts mapped across 3 or more samples. For IA-UW4, 3549 genes of a total

3919 predicted genes remained after applying this filter, and for IIC-UW6, 4297 genes of

a total 4877 predicted genes remained after applying this filter. We analyzed expression

patterns of differentially expressed genes using a threshold cutoff of ±1.5 log2 fold-

change between anaerobic and aerobic conditions and then identified differentially

expressed genes as core or accessory among clades IA (str. UW4) and IIC (str. UW6).

For the core group analysis, the corresponding ortholog in each genome had to meet the

minimum count threshold as described above to include in the comparison, with genes in

one or both of the strains being differentially expressed. For the accessory analysis for

each strain, the gene had to be differentially expressed and not contained in the other

genome but could be present in other strains or other genomes belonging to that clade.

Data and Code Availability

Raw sequencing files for the three metagenomes and seven metatranscriptomes

and genome assemblies for the four Accumulibacter genomes are available at NCBI

under the BioProject accession PRJNA668760. All genome assemblies used in this study

in their current forms as well as transcriptomic count tables are available at:

https://figshare.com/projects/Metabolic_Plasticity_of_Accumulibacter_Clades/90614. All

code is available at https://github.com/elizabethmcd/R3R4.

RESULTS

Enrichment of Co-Existing Accumulibacter Clades

We inoculated a 2-L sequencing-batch reactor with activated sludge from a full-

scale wastewater treatment plant in Madison, WI, USA and maintained operation for 40

months. The reactor was primarily fed with acetate and operated under cyclic anaerobic-

aerobic phases with a 4-day solids retention time to simulate the EBPR process and

enrich for Accumulibacter (Figure 1). During a period of stable EBPR (14 months following

inoculation) in which acetate was completely diminished by the start of the aerobic phase

and soluble phosphate was below 1.0 mg-L^{-1} at the end of the aerobic phase, we collected

seven samples across a single cycle (three in the anaerobic phase, four in the aerobic

phase) for RNA-sequencing (Figure 1A). We performed qPCR of the *ppk1* as described

previously (23) to quantify Accumulibacter clades present in the reactor on the same day

as the RNA-seq experiment (Figure 1B). At the time of the RNA-seq experiment, the

bioreactor was primarily enriched in Accumulibacter clade IA, followed by clade IIC and

clade IIA.

From metagenome samples collected from this bioreactor earlier, we assembled

high-quality genomes of belonging to four different Accumulibacter clades (Table 1),

including the dominant IA and IIC (strains IA-UW4 and IIC-UW6, respectively) clades and

the less abundant IIA and IIF clades (strains IIA-UW5 and IIF-UW7, respectively) (Figure

2). Each of the assembled genomes falls within the established Accumulibacter clade

nomenclature as defined by *ppk1* sequence identity and phylogenetic placement when

compared to other publicly available Accumulibacter genomes and clone sequences

(Figure 2A). Additionally, the *ppk1* hierarchical structure is also reflected by pairwise-

average nucleotide identity (ANI) boundaries between clades, with some exceptions for

newly assembled Accumulibacter genomes that fall outside of the established '*C.*

Accumulibacter phosphatis' lineage (Figure 2B). All assembled genomes are above 90%

complete and contain less than 5% redundancy as calculated by CheckM (44) (Table 1).

We were able to scaffold the assemblies of strains IIA-UW5 and IIC-UW6 using long

Nanopore reads, constructing a completely contiguous draft genome of the IIC-UW6

strain. To our knowledge, the assembled IIC-UW6 genome is the most contiguous,

highest-quality reference genome available for this clade, providing a valuable new

Accumulibacter reference genome (Figure 2C).

Distribution of Shared and Flexible Gene Content between Clades

We characterized the functional diversity of different Accumulibacter clades

through clustering orthologous groups of genes (COGs) (Figure 3A). We repeated a

COGs analysis from Skennerton et al. (26) and Oyserman et al. (67), but included an

updated set of high-quality Accumulibacter references, the UW-generated genomes, and

the outgroups *Dechloromonas aromatica* and *Rhodocyclus tenuis* (Figure 3). The

Accumulibacter lineage exhibits a tremendous amount of functional diversity, with only approximately 25% of COGs shared amongst all Accumulibacter clades (Figure 3A). Additionally, there is extensive diversity within the two Accumulibacter types and within individual clades, with only a few representatives of each clade more than approximately 75% similar to each other by gene content (Supplementary Figure 1). Specifically, clade IIC broadly harbors the most diversity of all sampled genomes by gene content, with representatives of this clade not sharing more than 25% of COGs (Figure 3A). Other clades are more similar by gene content, but this could be due to fewer genomes sampled from these clades. Most of the highest-quality, publicly available Accumulibacter genome references belong to clades IIF and IIC.

We then compared COGs between Accumulibacter clades collected from bioreactors seeded from the Nine Springs Wastewater Treatment Plant in Madison, as these genomes represent a shared origin (Figure 3B). In addition to two lab-scale bioreactors harboring distinct Accumulibacter clades (strains UW1 and UW3, and UW4-7, respectively) (22, 24), we recently characterized clade IC (strain UW-LDO-IC) using genome-resolved metagenomics and metatranscriptomics (14). Overall, genomes in Type I and Type II cluster respectively, where genomes within Type I are overall more similar to each other, as expected (Supplementary Figure 1). Clade IIA genomes (strains UW1 and UW5) were assembled from separate enrichments derived from the same full-scale treatment plant approximately 12 years apart, but are very similar by COG presence/absence (Supplementary Figure 1). UW genomes within Type II are less similar by gene content and seem to be more diverse in this regard, though again this could be due to under-sampling of Type I (8 genomes in Type I and 14 in Type II). Additionally,

clade IIF contains more overlap in gene content with Type I genomes in gene families

than some Type II genomes do to each other (Supplementary Figure 1).

COG overlap and uniqueness is shown by the intersection of COG groups between

UW Accumulibacter clades and the *Rhodocyclus* and *Decholoromonas* outgroups (Figure

3B). There are 1075 gene families shared among all UW Accumulibacter clades and

outgroup genomes, with 277 separate gene families only within the UW Accumulibacter

clades (Figure 3B). Among individual clades, there are 887 groups only within clade IIC

(UW6), 399 within clade IIA (UW1 and UW5), 399 within IIF (UW7), 292 within clade IA

(UW3 and UW4), and 196 within IC (UW-LDO). Although clade IIC str. UW6 contains

more overlap in gene content with SK-02 (Figure 3A), the intersection analysis (Figure

3B) identified gene families that are available to individual strains within the same

bioreactor ecosystem, highlighting the potential for functional differentiation.

Transcriptional Profiles of Accumulibacter Strains

Although *ppk1* locus quantification showed that the bioreactor was mostly enriched

in clade IA (see Figure 1B), surprisingly, more RNA-seq reads mapped to the clade IIC-

UW6 genome than to the clade IA-UW4 (Figure 4A). Approximately 40 million total

transcriptional reads aligned to the strain IIC-UW6 genome across the full time-series

experiment, whereas strains IA-UW4 and IIA-UW5 recruited roughly the same number of

reads, with 14 million and 11 million, respectively (Table 2). Markedly lower read levels

mapped to the IIF-UW7 strain relative to the other three clades, and therefore we do not

include the IIF-UW7 strain in our subsequent analyses. We explored the top differentially

expressed genes in strain IIC-UW6, comparing anaerobic and aerobic conditions (Figure

4B). Genes upregulated in the anaerobic phase belonged to pathways for central-carbon

transformations, fatty acid biosynthesis, and PHA synthesis. Interestingly, all genes within

the high-affinity phosphate transport system Pst were upregulated in the aerobic phase.

This includes the substrate-binding component *pstS, phoU* regulator, and the ABC-type

transporter *pstABC* complex (Figure 4B).

The co-existing clades in the bioreactor system differ in both the presence of sets

of nitrogen cycling gene sets and their expression profiles (Figure 4C). In strain IA-UW4,

we detected the *napAGH* genes for nitrate reduction, whereas we did not detect *napB*,

possibly due to these genes being close to the end of a contig in this genome. We also

detected a *nirS*-like nitrite reductase*,* both subunits of the nitric oxide reductase *norQD,*

and the nitrous oxide reductase *nosZ* in strain IA-UW4. Most of these genes in strain IA-

UW4 exhibit the highest expression patterns in the early and late anaerobic stages

(Figure 4C). Conversely, strain IIC-UW6 contains the *narGHIJ* machinery for nitrate

reduction, a different *nirS*-like nitrite reductase than in IA-UW4, and does not contain a

nitrous oxide reductase. However, strain IIC-UW6 does contain the nitrite reductase *nirBD*

for reducing nitrite to ammonium, which is uniformly expressed across the cycle (Figure

4C).

Expression Dynamics of Genes Shared by Strains IA-UW4 and IIC-UW6

When characterizing expression dynamics of COGs shared between strains IA-

UW4 and IIC-UW6, we found very few orthologs that exceeded the 1.5-fold change cutoff

for differential expression in both strains (Figure 5). These genes include a

coproporphyrinogen III oxidase, NAD-reducing HoxS subunits, the *phaC* subunit of the

PHA synthase, the long-chain fatty-acid-CoA ligase FadD13, and several hypothetical

proteins. The fatty-acid CoA-ligase incorporates ATP, CoA, and fatty acids of variable

length to form acyl-CoA to be degraded for energy production, incorporated into complex

lipids, or used in other metabolic pathways (68). The acyl-CoA ligase is upregulated in

the anaerobic phase of both clades, suggesting a role in anaerobic carbon metabolism,

as acyl-CoA can ultimately form acetyl-CoA through beta-oxidation. The *phaC* subunit of

the PHA synthase is differentially expressed in the anaerobic phase for both clades, as

is typical of the hallmark EBPR metabolism for Accumulibacter (13, 69).

Additionally, both the IA-UW4 and IIC-UW6 strains carry most of the subunits for

the bidirectional NiFe Hox system, encoding an anaerobic hydrogenase. The HoxH and

HoxY beta and delta subunits form the hydrogenase moiety, and the FeS-containing

HoxF and HoxU alpha and gamma subunits catalyze NAD(P)H/NAD(P)+

oxidation/reduction coupled to the hydrogenase moiety (70–72). In both clades, the FeS

cluster HoxF and HoxU alpha and gamma subunits are strongly differentially expressed

in the anaerobic phases, as was observed previously in a genome-resolved

metatranscriptomic investigation of strain IIA-UW1 (13). However, the IIC-UW6 genome

is missing the HoxY delta subunit of the hydrogenase moiety, and only strain IA-UW4

exhibits differential expression of the HoxH beta subunit in the anaerobic phase. Strain

IIC-UW6 does exhibit higher expression of HoxH in the late anaerobic and early aerobic

phases but does not meet the threshold cutoff for differential gene expression. A prior

study focused on strain IIA-UW1 also demonstrated hydrogenase activity in the anaerobic

phase, and then demonstrated hydrogen gas production after acetate addition (13). The

hydrogen gas production was hypothesized to replenish NAD+ after glycogen

degradation. Subsequent comparative genomics analysis suggested that the Hox system

is an ancestral state of Accumulibacter (67). Furthermore, recent metabolic models which

integrated hydrogen production under periods of excess acetate or glycogen were better

able to capture the diversity of observed EBPR stoichiometry (73). In this ecosystem,

both strains may exhibit anaerobic hydrogenase activity and thus produce hydrogen, but

due to the missing subunit in the IIC-UW6 genome and lack of differential gene

expression, this is uncertain.

Interestingly, only one strain exhibited differential expression patterns of several

core ortholog subsets important for EBPR-related functions exhibit. For example, subunits

of the high-affinity phosphate transporter Pst system are only differentially expressed in

strain IIC-UW6 and not IA-UW4, as observed for strain IIC-UW6 above (see Figure 4B).

Additionally, nitrogen cycling genes that contain orthologs in both clades display different

expression profiles. A nitrite reductase is only differentially expressed in the anaerobic

phase in strain IA-UW4 and the denitrification protein NirQ is differentially expressed in

only strain IIC-UW6. Whereas the nitrogen fixation protein subunit NifU is differentially

expressed in both strains. To activate acetate to acetyl-CoA, the high-affinity acetyl-CoA

synthase (ACS) or low-affinity acetate kinase/phosphotransacetylase (AckA/Pta)

pathways can be employed. The strain IA-UW4 assembly is missing an acetate kinase,

and phosphate acetyltransferase is only differentially expressed in this strain but not in

IIC-UW6. Within strain IIC-UW6, both the acetate kinase and phosphate acetyltransferase

genes exhibit relatively low levels of expression over the time-series. Both strains contain

several acetyl-CoA synthases that are highly expressed in the anaerobic phase,

particularly upon acetate contact, but do not exhibit notable differences in differential

expression between the two phases. Previous work based on community proteomics and

enzymatic assays have suggested that although both activation pathways are present

and expressed in Accumulibacter, the high-affinity pathway is preferentially used (74, 75).

Although a phosphate acetyltransferase is differentially expressed in strain IA-UW4, this

gene has lower transcripts relative to the acetyl-CoA synthase, providing more evidence

that the lineage (specifically both clades IA and IIC) may employ the high-affinity system.

Differential Expression of Flexible Genes in Strain IA-UW4

We lastly characterized expression dynamics of flexible gene content in strain IA-

UW4 (Figure 6). Since a majority of the differentially expressed flexible genes in strain

IIC-UW6 were annotated as hypothetical proteins, we focused on putative differentiating

features of clade IA-UW4. Flexible gene content for IA-UW4 can be defined as any

ortholog that is not present in the IIC-UW6 genome, whether or not that ortholog is only

contained within clade IA genomes, Type I as a whole, within other Type II or clade IIC

genomes, or the *Dechloromonas* or *Rhodocyclus* outgroups. Thus, the absence of a

particular ortholog in the strain IIC-UW6 genome but present in the IA-UW4 genome or

any other genomes was inferred as a lack of functional capability of IIC-UW6 in this

particular ecosystem.

Particularly striking is the differential expression profiles of nitrogen cycling genes

that do not contain orthologs in the IIC-UW6 genome. As stated above, clade IA-UW4

contains the *nap* system whereas strain IIC-UW6 contains the *nar* system for reducing

nitrate to nitrite (Figure 4C). In strain IA-UW4, the *napDGH* subunits are differentially

expressed between the anaerobic and aerobic phases, and these genes are present in

the outgroups, as well as both Accumulibacter types except the IIC-UW6 genome (Figure

6). Both genomes contain a *nirS* nitrite reductase, but the respective homologs are not

within the same COG, and thus strain IA-UW4 contains a different *nirS* that is upregulated

in the anaerobic phase. Strain IIC-UW6 does not contain both subunits of the nitric-oxide

reductase *norQD,* whereas strain IA-UW4 does. These subunits are not differentially

expressed above the set threshold but do exhibit the highest expression upon acetate

contact in the anaerobic phase (see Figure 4B). Additionally, strain IIC-UW6 does not

contain the nitrous-oxide reductase *nosZ* (see Figure 4B)*,* whereas strain IA-UW4 does,

and this is differentially expressed in the anaerobic phase (Figure 6). These results

suggest that strain IA-UW4 may have the capability for full denitrification from nitrate to

nitrogen gas, or at least use the reduction of nitrate/nitrite as a source of energy in the

anaerobic phase in a denitrifying bioreactor. Although strain IIC-UW6 does contain the

nirBD nitrite reductase complex for reducing nitrite to ammonium, these genes are

uniformly expressed throughout the cycle (see Figure 4B).

DISCUSSION

In this work, we performed time-series transcriptomics to explore gene expression

profiles of Accumulibacter strains belonging to clades IA and IIC, which co-existed within

the same bioreactor ecosystem. By applying genome-resolved metagenomic and

metatranscriptomic techniques, we were able to postulate niche-differentiating features

of distinct Accumulibacter clades based on core and accessory gene content and

differential expression profiles. We assembled high-quality genomes from four

Accumulibacter clades and used long reads to generate a single contiguous scaffold of

the IIC-UW6 genome. By performing an updated clustering of orthologous groups of

genes analysis, we were able to better demonstrate the similarity and uniqueness among

Accumulibacter strains from this system. Unexpectedly, although clade IA dominated in

abundance by *ppk1* locus quantification, clade IIC was more transcriptionally active. By

comparing the expression profiles of COGs shared between strains IA-UW4 and IIC-

UW6, we found that genes involved in EBPR-related pathways may differ between the

strains with respect to transcription-level regulation. Notably, strain IIC-UW6 showed a

strong upregulation of the high-affinity Pst phosphorus transport system in the aerobic

phase. High transcription of the Pst system in IIC-UW6 towards the end of the aerobic

phase when phosphorus concentrations were lower suggests that the IIC-UW6 strain was

more sensitive to bulk phosphate concentrations. This would be congruent with

specialization to relatively low phosphorus conditions. Whereas lack of differential

expression of the Pst system in IA-UW4 suggests this strain is more specialized under

high phosphorus conditions. Strain IA-UW4 contains most of the subunits for the

individual key steps for denitrification, and exhibits strong anaerobic upregulation of these

genes, suggesting a differentiating role for strain IA-UW4 in nitrogen cycling under

denitrifying conditions. Additionally, the IA-UW4 strain contains all subunits for encoding

the Hox anaerobic hydrogenase system, which exhibits upregulated gene expression in

the anaerobic phase. However, the IIC-UW6 strain is missing one of the subunits even

though the other subunits were expressed (but not differentially). Production of hydrogen

gas could be a differentiating role for the IA-UW4 strain, as this would impact potential

interactions with diverse flanking community members in addition to replenishing NAD+

(13, 24, 76).

The Accumulibacter lineage harbors extensive diversity between and amongst

individual clades which is exhibited not only by *ppk1*-based phylogenies, but also by

pairwise genome-wide ANI and COG comparisons. For example, strain IIA-UW1 and

strain IA-UW3 were present in the same bioreactor ecosystem and only share 85% ANI

(22). In the bioreactor enrichment from this study, the dominant strains IA-UW4 and IIC-

UW6 share less than 80% ANI (Figure 2B). Recently, a cutoff of >95% ANI has been

suggested to delineate distinct bacterial species or cohesive genetic units (49), which is

based on observations of coverage gaps at 90-95% sequence identity when

metagenomic reads were mapped back to assembled MAGs (77–80). These sequence

cutoffs have also been benchmarked against homologous recombination rates and ratios

of nonsynonymous to synonymous (*dN/dS*) nucleotide differences (81). Among

Accumulibacter genomes adhering to the established *ppk1*-based phylogeny, genomes

within individual clades fall within the >95% ANI threshold, whereas ANI comparisons

within and between Types I and II are more variable (Figure 2B). Genomes within Type I

are similar by approximately 90% ANI, whereas genomes within Type II are not as

coherent.

The apparent coexistence of diverse Accumulibacter clades within an ecosystem

then raises questions of ecological roles, putative interactions, and evolutionary dynamics

of this lineage over time and space. The ecotype model of speciation suggests that

cohesive, ecologically distinct ecotypes can coexist because they occupy separate niche

spaces (3, 82). Because Accumulibacter has not been isolated in pure culture to date,

most ecological and evolutionary inferences have been made from genome-based

comparisons (26, 67) or mapping metagenomic reads back to assembled genomes with

minimum percent identity cutoffs that may not sufficiently distinguish among sub-clades

(83, 84). However, the apparent diversity within the Accumulibacter lineage may require

reevaluation of the phylogeny and taxonomy overall. Although the *ppk1*-based clade

designations coincide with genome-wide ANI based cutoffs remarkably well

(Supplementary Figure 2B), there are some discrepancies. A few Accumulibacter

genomes have been assembled that do not adhere to the *ppk1*-based population

structure but fall within the Accumulibacter lineage based on a species tree of single-copy

core genes (Supplementary Figure 2A), such as the proposed novel species '*Candidatus*

Accumulibacter aalborgensis' (85). Additionally, a few genomes preliminarily classified by

the Genome Taxonomy Database (GTDB) as Accumulibacter branch outside of the

established nomenclature and are quite divergent based on the species and *ppk1*

phylogenies as well as genome-wide and *ppk1* sequence similarities (Figure 2B,

Supplementary Figure 2). Overall, substantial work is needed to reevaluate the

phylogenetic structure of the Accumulibacter lineage as a whole and to connect with

signatures of homologous recombination and evolutionary trajectories within coexisting

clades to understand the genetic boundaries and thus ecological interdependencies of

individual clades or strains.

Although the boundaries of individual Accumulibacter clades or strains have not

been entirely resolved to infer separate ecotypes, denitrification capabilities of specific

clades have been repeatedly suggested to be a niche-differentiating feature (14, 23, 25).

Previously, two separate bioreactors fed with either acetate or propionate as the sole

carbon source were enriched with different Accumulibacter morphotypes, which were also

linked to different denitrification capabilities (28). A study with a bioreactor highly enriched

in clade IC inferred simultaneous use of oxygen, nitrite, and nitrate as electron acceptors

under micro-aerobic conditions either due to metabolic flexibility or heterogeneity within

IC members (23). The resident strain IC-UW-LDO also possessed the full suite of genes

for denitrification and expressed them in microaerobic conditions (14). Coexisting

Accumulibacter strains with differing denitrifying abilities have also been observed in a

denitrifying EBPR bioreactor enriched in clade IA and clade IC (17, 27). The clade IA

strain encoded genes for complete denitrification, whereas the co-occurring clade IC

strain and other flanking community members did not (27). Additionally, Gao et al.

performed an ancestral genome reconstruction analysis similar to Oyserman et al. 2017

(67) to specifically understand the flux of denitrification gene families (27). The *nir* gene

cluster was identified as a core COG to all sampled Accumulibacter genomes, whereas

the periplasmic nitrate reductase *napAGH* and nitrous oxide reductase *nosZDFL* clusters

were core to only Type I Accumulibacter genomes, and inferred to have been lost for

some Type II genomes (27). Additionally, Wang et al. subsequently observed that an

internal stop codon within the open reading frame of the *nosZ* gene in a clade IC strain

coincided with decreased transcripts mapping back (17, 27). In our study, we observed

differential expression of denitrification genes in strain IA-UW4 but not strain IIC-UW6.

These expression differences could explain why the two strains can coexist and

contribute to overall ecosystem functioning (e.g. phosphorus removal) by using different

electron acceptors in the anaerobic/aerobic conditions. Although the synthetic feed for

the bioreactors in this study inhibits ammonia oxidation through allylthiourea addition (and

thus inhibits nitrite/nitrate production to fuel respiratory denitrification), the expression

profiles of denitrification genes in strain IA-UW4 suggests this strain is equipped to have

a differentiating role in a denitrifying bioreactor. We specifically observed differential

expression of nitrate reductase and nitrous-oxide reductase genes in strain IA-UW4,

where homologs of these genes were not present in the strain IIC-UW6 genome and other

Type II genomes. From our work and previous studies, lack of the complete genetic

repertoire for denitrification among and within individual clades in addition to

transcriptional-based evidence suggests that denitrification capabilities could be a niche

differentiating role for specific Accumulibacter populations.

Accumulibacter's anaerobic metabolism has also been shown to differ under

varying substrate or stoichiometric conditions and possibly between the two

Accumulibacter types. Recent simulations of 'omics datasets paired with enzymatic

assays hint that the routes of anaerobic metabolism for Accumulibacter may differ based

on environmental conditions (73). Under high acetate conditions, polyphosphate

accumulation arises through the glyoxylate shunt, whereas under increased glycogen

concentrations, glycolysis is used in conjunction with the reductive branch of the TCA

cycle (73). Furthermore, Welles et al. found that Type II Accumulibacter can switch to

partial glycogen degradation more quickly than Type I, enabling Type II to fuel VFA uptake

in polyphosphate-limited conditions (86, 87). Conversely, when concentrations of

polyphosphate are high, VFA uptake rates are higher in Type I. However, these studies

only identified Accumulibacter lineages based on *ppk1* types, and therefore extrapolated

metabolic assumptions from presumably more resolved strains to the entire type. These

broad interpretations may obscure apparent functional differences between the two types

and individual clades. Future experiments could integrate multi-'omics approaches to

investigate not only metabolic flexibility under different substrate conditions and

perturbations but also how metabolisms are distributed amongst Accumulibacter clades

in bioreactor ecosystems that are not completely enriched in a single clade or strain and

elucidate key functional differences.

CONCLUSIONS

In this study, we integrated genome-resolved metagenomics and time-series

metatranscriptomics to understand gene expression patterns of co-existing

Accumulibacter strains within a bioreactor ecosystem. We found evidence for

denitrification gene expression in the dominating IA-UW4 strain, but higher overall

transcriptional activity for the IIC-UW6 strain along with differential expression of a high-

affinity phosphorus transporter. The coexistence of Accumulibacter populations exhibiting

different gene expression patterns for phosphorus and nitrogen cycling and hydrogen

productions suggest niche differentiating features and contribution to different metabolic

programs. Detailed experiments incorporating microautoradiography combined with

fluorescence in situ hybridization (MAR-FISH) could be applied to confirm metabolic

activities of coexisting Accumulibacter populations and how they contribute to important

EBPR-related functions (88). These results also highlight the need to reevaluate the

phylogenetic structure of the Accumulibacter lineage and define how potential genetic

boundaries may translate to individual ecological niches that allow for the coexistence of

multiple clades, species-like groups, or strains. Additionally, we highlight an approach for

exploring functions of co-existing species-like uncultivated microbial lineages by exploring

gene expression patterns of shared and accessory genes. Overall, this work emphasizes

the need to understand the basic ecology and evolution of microorganisms underpinning

biotechnological processes, which can lead to better treatment process control and

resource recovery outcomes in the future (89).

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FIGURE AND TABLE LEGENDS

Figure 1. Overview of Experimental Design and Enriched Accumulibacter Clades.

1A. Overview of EBPR cycle and sampling scheme. Samples were collected for RNA sequencing over the course of a normal EBPR cycle, with reported measurements for soluble phosphorus and acetate normalized by volatile suspended solids (VSS). Samples were taken at time-points 0, 31, 70, 115, 150, 190, and 250 minutes. **1B.** Abundance of different Accumulibacter clades by *ppk1* copies per ng of DNA. Quantification of Accumulibacter clades was performed by qPCR of the *ppk1* gene as described in Camejo et al. (23).

Figure 2. Assembly of Four High-Quality Accumulibacter Genomes

2A. Phylogenetic tree of *ppk1* nucleotide sequences from available Accumulibacter reference genomes, clone sequences, and the four assembled Accumulibacter genomes from this study. Tips in bold represent *ppk1* sequences from metagenome-assembled genomes, whereas others are sequences from clone fragments available at the referenced accession numbers. Starred tips represent *ppk1* sequences from the four assembled Accumulibacter genomes from this study. Tree was constructed using RaXML with 100 rapid bootstraps. **2B.** Pairwise genome-wide ANI comparisons of all publicly available Accumulibacter references and the four new Accumulibacter genomes, denoted in bold. Genomes are grouped according to clade designation by *ppk1* sequence identity and in order of the *ppk1* phylogeny, except for those that do not fall in an established clade. **2C.** Genome diagram of the UW6 Accumulibacter IIC MAG (98.6% completeness,

2.5% contamination, 5.18 Mbp). Layers represent from top to bottom: coverage over 1000

bp windows, GC content and skew across the same 1000 bp windows, coding sequences

on the positive and negative strands, and positions of predicted rRNA (red) and tRNA

(black) sequences.

Figure 3. Core and Flexible Gene Content among the Accumulibacter lineage and

UW genomes

3A. Phylogenetic tree of the coding regions for the *ppk1* locus among high-quality

Accumulibacter references, UW genomes, and outgroup taxa *Dechloromonas aromatica*

RCB and *Rhodocyclus tenuis DSM 110.* The pie graph at each node represents the

fraction of genes that are shared and flexible for genomes belonging to that clade. **3B.**

Upset plot representing the intersections of groups of orthologous gene clusters among

UW genomes and outgroups, analogous to a Venn diagram. 1075 gene families were

shared among all UW Accumulibacter clades and outgroup genomes and 277 separate

gene families were found only within the UW Accumulibacter clades. Each bar represents

the number of orthologous gene clusters, and the dot plot represents the genomes in

which the groups intersect.

1006

Figure 4. Transcriptomic Profiles of Accumulibacter Clades

4A. Average expression profiles of each reference genome in the anaerobic and aerobic

phases. The IIC-UW6 genome mapped the most transcripts even though the IA-UW4 was

more abundant. Reads were competitively mapped to the four assembled Accumulibacter

clade genomes and normalized by transcripts per million (TPM). The sum of the

normalized counts of the three samples in the anaerobic phase and four samples in the

aerobic phase were averaged, respectively, and plotted on a $\log_{10}$ scale. Numbers and

percentages for adjacent to normalized bars represent the raw number of reads that are

mapped to each genome. **4B.** Top 50 differentially-expressed genes in clade IIC-UW6.

All 50 genes pass the threshold of ± 1.5 log-10 fold-change across the cycle. Annotations

were predicted from a combination of Prokka (45) and KofamKOALA (46). **4C.**

Denitrification gene expression among clades IIC-UW6, IA-UW4, and IIA-UW5. We

summarized expression for genes involved in denitrification by highlighting parts of the

cycle in which certain genes are expressed the most. This is characterized by acetate

contact (pink), early anaerobic (dark purple), late anaerobic (purple), early aerobic (dark

blue) and late aerobic (light blue), where uniform describes uniform expression across

the entire cycle (grey). If an arrow is missing for a step, that particular clade did not contain

confident annotations within the genome for those genes. For nitrate reduction, the *nar*

system is represented as a black dot and the *nap* system is represented as a grey dot.

Multiple arrows are shown for a single step in which particular genes were highly

expressed in multiple phases.

1028

Figure 5. Differential Expression of Shared Genes in Strains IA-UW4 and IIC-UW6

Gene expression profiles of core COGs across the EBPR cycle that are differentially

expressed between anaerobic and aerobic conditions in either IA-UW4 or IIC-UW6 or

both strains. To consider a gene differentially expressed in a strain, the COG must exhibit

± 1.5 fold-change in expression between anaerobic and aerobic phases. Homologs that

are directly compared to each other in IA-UW4 and IIC-UW6 are orthologous genes that

belong to the same cluster.

1036

Figure 6. Differential Expression of Accessory Genes in Strain IA-UW4

Gene expression profiles of groups of accessory gene groups in strain IA-UW4 that are

not present in the IIC-UW6 genome. A gene was considered differentially expressed

between the anaerobic and aerobic conditions if it exhibited greater or less than ± 1.5 fold-

change in expression. Colored dots represent whether or not that gene contains orthologs

within outgroup genomes, other Type II Accumulibacter other than the IIC-UW6 genome,

within Type I Accumulibacter, or only within IA.

1044

1045   **Table 1. Assembled Accumulibacter Genome Statistics**

1046   Genome quality calculations for completeness and contaminations were made with

1047   CheckM based on the presence/absence of single-copy genes (44).

1048

1049   **Table 2. Metatranscriptomic Reads Mapped to Accumullibacter Genomes**

1050   Counts of raw metatranscriptomic reads mapped to each Accumulibacter genome with

1051   kallisto (65) in each sample for the three anaerobic samples and four aerobic samples

1052   and total reads mapped for all samples.

1053

Supplementary Figure 1.

Pairwise Pearson correlation coefficient of shared gene content as a measure of how

similar each of the UW genomes is to each other based on COGs.

Supplementary Figure 2.

S2A) Species tree of all Accumulibacter reference genomes, UW-assembled genomes,

and outgroup genomes using single-copy markers from the GTDB-tk (50). A phylogenetic

tree was constructed using RAxmL with 100 rapid bootstraps and visualized in iTOL. **S2B)**

Pairwise BLAST percent identity scores for *ppk1* coding regions for each reference

genome in Figure 2B, in order of the *ppk1* phylogeny in Figure 2A. Raw pairwise percent

identity   scores   are   available   at

https://figshare.com/articles/dataset/Pairwise_Accumulibacter_ppk1_BLAST_Percent_D

_Scores/13237247.

1066

1067 **Supplementary Table 1**

1068 Genome accessions and statistics for all Accumulibacter references used in phylogenies,

1069 ANI comparisons, and COG calculations. A reference genome was used for COG

1070 comparisons if it was a high quality genome (>95% complete and <5% redundant).

1071 Available at https://figshare.com/account/projects/90614/articles/13237148

1072

1073 **Supplementary File 1**

1074 Raw pairwise genome-wide ANI results for each genome calculated with FastANI.

1075 Available at https://figshare.com/account/projects/90614/articles/13237244

1076

1077 **Supplementary File 2**

1078 Raw pairwise BLAST percent identity (PID) results for *ppk1* genes from each reference

1079 genome. Available at https://figshare.com/account/projects/90614/articles/13237247

A.

B. **Strain IIC-UW6**

C.

	UW3-IA	UW4-IA	UW-LDO-IC	UW5-IIA	UW1-IIA	UW6-IIC	UW7-IIF
UW3-IA	100.0%	78.3%	62.9%	40.9%	40.4%	33.3%	48.8%
UW4-IA	78.3%	100.0%	57.2%	34.0%	33.3%	29.2%	41.5%
UW-LDO-IC	62.9%	57.2%	100.0%	40.0%	40.0%	35.7%	48.7%
UW5-IIA	40.9%	34.0%	40.0%	100.0%	92.3%	35.7%	52.0%
UW1-IIA	40.4%	33.3%	40.0%	92.3%	100.0%	36.0%	50.1%
UW6-IIC	33.3%	29.2%	35.7%	35.7%	36.0%	100.0%	40.9%
UW7-IIF	48.8%	41.5%	48.7%	52.0%	50.1%	40.9%	100.0%

A.

Clade IA

Clade IB
Clade IC

Clade IIA

Clade IIC

Clade IIF

Tree scale: 0.01 ⊢—⊣

B.

Pairwise
BLAST %
Identity Score
of *ppk1*

Clade IIF

Clade IIC

Clade IIA

Clades IB & IC

Clade IA

Genome	Completion	Contamination	Size_Mbp	Contigs	GC
IIA-UW5	98.99	5.24	4.88	68	64.3
IIC-UW6	98.57	2.46	5.18	1	61.1
IIF-UW7	98.97	3.04	4.87	102	66.3
IA-UW4	92.90	3.37	4.29	358	64.0

Clade Genome	Anaerobic-10:45	Anaerobic-11:16	Anaerobic-11:55	Aerobic-12:40	Aerobic-13:15	Aerobic-13:55	Aerobic-14:55	Total Reads Mapped
IIA-UW5	1063676	1357480	1706229	2197556	1763359	1171470	2065179	11324949
IIC-UW6	5226724	5892548	6755519	7902549	5004518	6914956	4132969	41829784
IIF-UW7	51038	78249	84520	121226	86070	90567	63866	575537
IA-UW4	1484341	2216299	2290441	3362431	1950259	1558605	1157345	14019720