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Metabolic specialization drives reduced pathogenicity in *Pseudomonas aeruginosa* CF clinical isolates

Bjarke H. Pedersen [1], Filipa B. Simões [2], Ivan Pogrebnyakov [1], Martin Welch [3], Helle Krogh

Johansen [1,2,4], Søren Molin [1] and Ruggero La Rosa [1,2#]

[1] The Novo Nordisk Foundation Center for Biosustainability, Technical University of Denmark,

2800 Kgs. Lyngby, Denmark

[2] Department of Clinical Microbiology 9301, Rigshospitalet, 2100 Copenhagen, Denmark

[3] Department of Biochemistry, University of Cambridge, CB2 1TN Cambridge, United Kingdom

[4] Department of Clinical Medicine, Faculty of Health and Medical Sciences, University of

Copenhagen, 2200 Copenhagen, Denmark

Address correspondence to Ruggero La Rosa, rugros@biosustain.dtu.dk

Abstract

Metabolism provides the foundation for all cellular functions. During persistent infections, in

adapted pathogenic bacteria it functions radically differently compared with more naïve

strains. However, whether this is simply a necessary accommodation to the persistence

phenotype or if metabolism plays a direct role in achieving persistence in the host is still

unclear. Here, we characterize a shift in metabolic functions aligned with a persistence

phenotype occurring in eight infection scenarios of *Pseudomonas aeruginosa* colonization of

people with cystic fibrosis. We identify clinical mutations in the key metabolic enzyme

pyruvate dehydrogenase leading to a host specialized metabolism together with a lower

virulence and immune response recruitment. This is mediated by impaired type III secretion

system activity and by secretion of the antioxidant metabolite, pyruvate. These results

provide evidence for the direct adaptiveness of metabolism during a persistent infection and

its intrinsic role in supporting pathogenicity.

Introduction

Metabolism of bacterial pathogens is a central process involved both in cell duplication and

in virulence. In several infections, nutrient composition of the host microenvironment

provides an environmental cue for bacterial pathogens to activate their virulence repertoire

[1]. For instance, abnormalities in calcium homeostasis, nutrient limitation or change in pH

signals activation of the type III secretion system (T3SS) cascade in several bacterial species [2–

5]. Similarly, metabolism dependent processes such as biofilm production and mucoidy provide

shielding from antibiotics and immune cells, and are generally associated with worse

prognosis [6–8]. Furthermore, crosstalk between bacteria and immune cells through exchange

of bacterial and host metabolites has additionally revealed the importance of metabolism in

determining the outcome of an infection [9–11].

However, metabolism is not a static function; it dynamically changes to support cell growth

and virulence specifically for each host and type of infection. For example, clinical strains of

Pseudomonas aeruginosa that infect people with cystic fibrosis (pwCF), have been shown to

modify their metabolic preference to accommodate to the specific nutrient composition of

the airways [12,13]. Auxotrophy, specialized assimilation of carbon sources, secretion of high

value metabolites and differential oxygen requirements of adapted clinical strains ensure appropriate functionality of the cell and support the phenotype requirements in the host [14].

In persistent infections, genetic variants with high antibiotic resistance, tolerance to other stresses, host and immune evasion capabilities or low virulence are specifically selected for since they provide higher within-host fitness [16–18]. However, it is still unclear if and how metabolic specialization directly contribute(s) to persistence [12,21]. Few examples of laboratory studies in *P. aeruginosa* and *Escherichia coli* have suggested the involvement of specific metabolic mutations with changes in antibiotic susceptibility and virulence [22–26]. However, limited knowledge is available on their relevance and purpose in clinical isolates during an infection. Moreover, the extent to which metabolic specialization *per se* provides a specific fitness advantage or if it is merely a consequential metabolic adjustment caused by other essential phenotypes, still remains unknown. Furthermore, the specific selective forces (for example antibiotic treatment or the immune system) leading to metabolic specialization are still largely uncharacterized.

By analyzing in detail, the metabolic and proteomic profiles of clinical strains of *P. aeruginosa* at different stages of host adaptation from pwCF, we identified distinct metabolic configurations characterized by CF-specific nutrient assimilation and secretion patterns. This was caused by changes in proteome allocation and metabolic mutation. Additionally, we characterized a specific metabolic specialization involving the pyruvate dehydrogenase complex (PDHc) which is essential for the processive flux of pyruvate through central carbon metabolism. Surprisingly, recombinant strains containing single mutations in the PDHc show decreased infection capabilities and immunogenicity in an Air-Liquid Interface (ALI) infection model system. These strains display a chronic-like phenotype and an increased secretion of pyruvate, which is an important scavenger of reactive oxygen species (ROS) and has known anti-inflammatory properties [27–29]. Importantly, these mutations are widespread in clinical isolates of *P. aeruginosa* suggesting that adaptation to the host environment and metabolic specialization might be specifically selected for during the early stages of an infection, thereby limiting host-dependent inflammation. Altogether these results provide a rationale for metabolic specialization during CF airway infections.

Results

Growth rate reduction as proxy for within-host adaptation

To gain insight on the metabolic adaptation occurring in *P. aeruginosa* clinical isolates during the infection of pwCF, we selected pairs of early (first *P. aeruginosa* isolated from the person) and late clinical isolates, longitudinally isolated from eight different pwCF and belonging to distinct clone types (> 10.000 SNPs difference) (Fig. 1a). Reduced growth rate was used as proxy for within-host evolution, enabling us to assemble a diverse and variegated collection of clinical isolates spanning between 1.4 and 7 years of within-host evolution (Table S1). When grown in SCFM medium (which has been formulated to resemble the CF mucus composition [15]), early isolates showed a high growth rate comparable to the reference strain, PAO1. Conversely, late isolates showed a 2.2- to 5.1-fold reduction in growth rate, in addition to a halved maximal optical density (paired t test, P = 0.002) (Fig. 1a-b). Moreover, some late isolates were unable to grow in minimal medium in presence of single carbon sources such as glucose, lactate or succinate, suggesting a certain level of metabolic constraint (Fig. 1c).

Despite belonging to distinct clone types, a certain degree of phylogenetic convergence is shown by early and late strains, since they tend to cluster closely within each group (early or late) rather than by their clone type (Fig. 1d). The distribution of mutations either accumulated or reverted during within-host evolution differs between clone types confirming different evolutionary trajectories in each host, including hypermutation events (Fig. 1e and Supplementary Data 1). However, mutated genes are similarly enriched between clone types (pyoverdine biosynthetic process for Gene Ontology (GO) categories and bacterial secretion system and porphyrin metabolism for Kyoto Encyclopedia of Genes and Genomes (KEGG) categories) confirming, as also shown in several other investigations [19,20], conserved targets of within-host evolution between infection scenarios (Fig. 1f).

Within-host evolution selects for specialized metabotypes

To evaluate the degree of metabolic specialization of the selected clinical isolates, dynamic exo-metabolomics was performed on cells growing in SCFM (Supplementary Data 2). PCA of the extracellular metabolomes reveals the presence of three distinct late specialized metabolic configurations, here defined as "metabotypes" (DK15 and DK55 metabotype 1;

DK12 metabotype 2; DK03, DK13 and DK36 metabotype 3). In these metabotypes, late

isolates separate from each respective early isolate and from the rest of the non-adapted

metabotypes (Fig. 2a). While PCA emphasizes the largest differences in the metabolome

profiles, hierarchical cluster analysis clearly separates early from late strains indicating a

certain degree of metabolic specialization in all late isolates (Fig. 2b). Indeed, both the

hierarchy of assimilation (metabolites half-life, OD_{50}) and the secretion of metabolites differs

between early and late isolates (Fig. 2c-d). Specifically, metabotype 1 shows reduced

assimilation of Lys, Gly, Ile, Leu, Phe, Thr, Tyr and Val and secretion of pyruvate by strain DK55

late; metabotype 2 shows increased assimilation of glucose, Ala, Asp, Glu, Gly, Pro, Ser, Arg

and His, and secretion of high amount of pyruvate; and metabotype 3 shows increased

assimilation of glucose and lactate, differential assimilation of Ala, Asp, Glu, His and Pro and

secretion of pyruvate by strain DK36 late (Fig. 2c-d). Late DK13, DK36 and DK41 strains secrete

a low concentration of formate whereas all late isolates secrete acetate, albeit at different

concentrations and with different growth-dependent profiles (Fig. 2d). Unsurprisingly, the net

balance between assimilated and secreted metabolites (total mM) varies between early and

late strains (Fig. 2e), which positively correlates with the lower biomass of the late isolates

(Pearson's r = 0.9; P = 0.0023) (Fig. 1b and 2e). This suggests either a specific metabolic

configuration for the late isolates, the objective of which is not biomass accumulation, or an

apparent inefficient metabolism.

Changes in proteome allocation supports the metabolic specialization of clinical isolates

To evaluate the contribution of the proteome composition to the metabolic specialization of

clinical strains, we performed whole cell proteomics to compare protein profiles between

strains. Of the 2061 proteins identified, 740 proteins were differentially expressed in at least

one comparison (early *vs* PAO1 or late *vs* early) (Supplementary Data 3). Similar to the

metabolomic analysis, PCA separates late from early proteomes suggesting that changes in

metabolite profiles might be rooted in the proteome (Fig. 3a, b). Most of the early and some

of the late proteomes colocalize with the reference strain PAO1 indicating little or no changes

in proteome allocation (Fig. 3a, b). However, proteomes of the late isolates of lineages DK12,

DK17, DK36, and DK55 separate from the respective early strains forming a cluster of adapted

proteomes (Fig. 3a, b). Notably, DK03 strains form an independent cluster, indicating a lineage

specific proteome signature which might depend in the already reduced growth rate of the

early isolate (Fig. 1a and 3a, b).

A similar result is obtained when performing hierarchical clustering analysis specifically on the

235 differentially expressed proteins between late and early strains belonging to the Clusters

of Orthologous Groups (COG) categories involved in metabolism. The adapted metabotypes

DK12, DK36 and DK55 and DK17 (cluster B) separate from the naïve metabotypes (cluster A)

supporting the hypothesis that metabolism specialization is likely rooted in changes in

expression of proteins involved in cellular metabolism (Fig. 3c). Notably, cluster B is

characterized by a higher number of differentially expressed proteins in the categories of

amino acids and lipid metabolism, and energy production and conversion relative to cluster

A (Fig. 3d and Fig. S1a). Similarly, several categories of proteins involved in the metabolism of

amino acids, fatty acid and sugars are statistically enriched in naïve and adapted clone types

(Fig. S1b) providing a molecular explanation for the altered hierarchy of assimilation of the

carbon sources and the reduced growth rate of the late adapted metabotypes (Fig. 2c, d).

Albeit late strains of DK12, DK36, DK55 belong to different metabotypes, their proteomes

move in the same direction (Fig. 3a-c). This indicates that largely similar proteomes can

sustain distinct metabolic configurations which ultimately depend on the metabolic fluxes

thorough specific pathways and on their regulation. Moreover, proteome adaptation can be

achieved without rewiring of metabolism as shown by strain DK17 which belongs to cluster B

(Fig. 3a-c), but does not present any major metabolic rewiring (Fig. 2a, b).

Interestingly, several enzymes belonging to the Entner-Doudoroff/Embden-Meyerhof-

Parnas/Pentose Phosphate (EDEMP), and tricarboxylic acid (TCA) cycle pathways are up-

regulated in the early and late strains relative to PAO1, indicating a specific and convergent

configuration of central carbon metabolism enzymes that are optimal for exploiting the

airway's resources (Fig. 3e and S2). For example, our metabolomic data show that several late

strains (belonging to metabotypes 2 and 3) exhibit increased glucose assimilation, which is in

agreement with the increased expression of pathways involved in glucose assimilation

(enzymes 3, 11, 12, 18) (Fig. 3e). Similarly, the fumarate hydratase (enzyme 33) together with

the enzymes involved in Trp, Phe and Tyr catabolism (enzymes 65 and 66) show increased

expression, likely to better accommodate the increased assimilation of amino acids which are

catabolized through the TCA cycle (Fig. 3e). This hypothesis is corroborated by the changes in

expression (both increased and decreased) in late *vs* early strains of several enzymes involved
in amino acids, glucose, and lactate catabolism and of their respective transporters (Fig. 3e).
This proteome configuration supports the hypothesis that overflow of amino acids through
central carbon metabolism, might be the cause of increased pyruvate secretion in late strains
of DK12, DK36 and DK55 (Fig. 2d and 3e).

Changes in virulence traits during within patient evolution

Analysis of the differentially expressed proteins enriched when comparing late *vs* early
isolates shows that most of the changes are directed toward adaptation to the infection
environment, and especially to redox balance and virulence (Fig. 4a and S1b). Indeed, the
categories of proteins showing expression changes in most of the lineages are phenazine
biosynthesis (KEGG) and secondary metabolite(s) biosynthetic process (GO) which are deeply
connected with cell homeostasis, metabolism and virulence [30,31]. Not surprisingly, several
clone types harbour mutations in genes belonging to the pyoverdine biosynthetic process
(GO) category (Fig. 1f), and several mutated genes shared between metabotypes belong to
the COG category of secondary metabolites biosynthesis, transport and catabolism (Fig. S1b).
Interestingly, several changes in protein expression are already shown by early strains relative
to PAO1 indicating a different response of clinical strains to the airway-like conditions of the
SCFM medium (Fig. 4a). Specifically, early strains show increased expression of proteins
involved in alginate production, hydrogen cyanide (HCN), phenazine biosynthesis and PQS
(*Pseudomonas* quinolone signal), and decreased expression of proteins involved in flagella
biogenesis, lipopolysaccharide (LPS) O-antigen metabolism and pyoverdine production, which
are all hallmarks of an acute phenotype (Fig. 4b). Instead, the adapted metabotypes, and
specifically strains belonging to cluster B, show convergent up-regulation of proteins related
to alginate, phenazine, PQS and the type VI secretion system (T6SS) suggesting an active role
of metabolism in virulence regulation and the chronic infection phenotype (Fig. 4c and S3).
Interesting, the DK12 late strain also shows lower expression (-1.5-fold) of the type III
secretion system (T3SS) secreted factor ExoT, the activity of which prevents phagocytosis and
induces cytoskeletal reorganization and host cell apoptosis [32,33]. Overall, the identified pattern
suggests a reduced immunogenicity of the clinical strains relative to PAO1, and an even

greater reduction in the late isolates. This is in line with their persistence during CF airway
infections.

aceE and aceF mutations leads to metabolic specialization and impaired virulence

Screening for mutations which could explain the metabolic specialization of the late isolates
and the lower expression of virulence determinants, led to the identification of mutations in
genes encoding the pyruvate dehydrogenase complex (PDHc), *aceE* and *aceF*, in late strains
of DK12 and DK36, respectively (Supplementary Data 1). The PDHc catalyses the conversion
of pyruvate into acetyl-CoA, connecting sugar metabolism to the TCA cycle (Fig. 3e).
Interesting, the *aceE* and *aceF* genes are candidate pathoadaptive genes and their *in-situ*
expression is reduced in sputum samples collected from chronically-infected pwCF [19,34]. This
suggests an undescribed role of the PDHc activity during infection.

To evaluate the contribution of *aceE* and *aceF* mutations to the bacterial phenotype,
independent of the underlying historical contingency of the clinical strains, we generated
recombinant PAO1 derivative strains containing the +TCCC duplication (position 813) in *aceF*
from the late DK12 strain, and the T→C SNP (position 551) in *aceE* from the late DK36 strain
(Fig 5a). The *aceF* mutation leads to a frameshift of translation starting from Lys 273, whereas
the *aceE* mutation leads to a Phe→Ser amino acid change. The recombinant *aceE* and *aceF*
mutant strains show reduced growth rate and increased secretion of pyruvate similar to that
of the DK12_L and DK36_L late strains (Fig. 1a, 2d and 5c). The *aceE* mutant strain shows a
milder phenotype (a smaller reduction in growth rate reduction and lower pyruvate secretion)
compared with the *aceF* mutant strain, suggesting partial functionality of the PDHc. Indeed,
supplementing acetate to the bacterial culture to replenish the pool of acetyl-CoA, fully
restored the growth phenotype of the *aceE* strain, whereas it only partially restored growth
in the *aceF* mutant strains (Fig. 5b). This confirms a much more significant effect of the *aceF*
mutation on the activity of the PDHc. Surprisingly, phenotypes such as biofilm formation,
motility, redox susceptibility, pyoverdine production and antibiotic susceptibility, were not
affected much, with no differences observed between the PAO1 wild-type strain and the *aceE*
and *aceF* mutant strains, except for a slight decrease in twitching motility and mildly increased
tobramycin susceptibility (Fig. S5). Screening for other *aceE* and *aceF* mutations in our strain

collection, we identified the presence of 18 different mutations (4 indels and 14 SNPs of which 3 silent) supporting the hypothesis that modulation of the PHDc might be selected for specifically during airway infections for reasons other than antibiotic resistance (Fig. S4).

To characterize the effect of the *aceE* and *aceF* mutations more broadly, we performed whole cell proteomics on the *aceE* and *aceF* recombinant strains (and on the PAO1 progenitor) in presence and absence of acetate. In total, we quantified 3246 proteins and identified 449 as differentially expressed in at least one comparison of either mutant *vs* wt strain or of mutant strain in presence *vs* absence of acetate (Supplementary Data 4). In the absence of acetate, the proteomes of the *aceE* and *aceF* mutant strains cluster in different quadrant compared with that of PAO1. PC1, which encompasses >50% of the variance in the dataset, separates the *aceF* strain proteome from that of PAO1, whereas less than 20% of the variance separates the proteome of the *aceE* strain from that of PAO1 along PC2 (Fig. 5d). As previously reported, the supplementation of acetate benefits both the *aceE* and *aceF* strains, with both proteomes moving closer to that of PAO1 (Fig. 5d). This effect is accentuated in the *aceF* mutant strain where the supplementation with acetate decreases the number of differentially expressed proteins by more than half (from 301 to 126) (Fig. 5e). Not surprisingly, several enzymes involved in central carbon metabolism and amino acid catabolism, and specifically those involved in pyruvate and acetyl-CoA metabolism (lactate dehydrogenase (41), acetyl-coenzyme A synthetase (6), citrate synthase (28)) are up-regulated in the *aceF* mutant strain whose expression returns to wild-type levels following the addition of acetate (Fig. 5f and S6a). As shown for the clinical isolates DK12_L and DK36_L, the categories of proteins involved in amino acid and lipid metabolism, and energy conversion presented the highest number of differentially expressed proteins (Fig. S6b). Similarly, proteins involved in terpene, propionate, isoprenoid and branched-chain amino acids (which are directly connected to pyruvate and acetyl-CoA metabolism) where statistically enriched in the *aceF* mutant strain indicating a reorganization of both central and peripherical pathways to cope with reduced synthesis of acetyl-CoA (Fig. S6c). Importantly, the *aceE* and *aceF* mutant strains show increased expression of proteins involved in alginate production and T6SS, and reduced expression of proteins involved in the T3SS, including the secreted factor ExoT (strain *aceF* and DK12_L) (Fig. 5g and Supplementary Data 4). This indicates that the *aceE* and *aceF*

mutations are the leading cause of the expression profile of virulence determinants shown by

the late clinical isolates of DK12 and DK36 (Fig. 4, 5g and Supplementary Data 4).

Pyruvate dehydrogenase mutations modulate pathogenicity in ALI culture infections

To test whether the reduced expression of virulence determinants in the *aceF* and *aceE*

mutant strains leads to reduced infectivity, we performed host-bacteria infections using an

ALI infection model system composed of mucociliated differentiated airway epithelial cells

and the recombinant *aceF* and *aceE* mutant strains. Overall, the *aceF* mutant strain displayed

a broad suppression of virulence, including reduced epithelium damage and innate immune

recognition during the infection (Fig. 6). The transepithelial electrical resistance (TEER) which

quantifies the integrity and permeability of the epithelial layer, LDH release which quantifies

the epithelium cellular damage, and the bacterial count which quantifies the growth and

penetration of the bacteria through the epithelium to the basolateral side of the ALI

transwells, all showed reduced values after 14 hours of infection when compared with the

PAO1 reference strain (Fig. 6a). This is in line with the behaviour of a *ΔpscC* mutant strain

defective in T3SS which shows a severely reduced virulence (Fig. 6a). By contrast, the *aceE*

strain, elicited similar epithelial damage to PAO1, indicating that the mutation does not

influence bacterial penetration (Fig. 6a). This is consistent with the proteomic analysis

showing no significant differential expression of proteins involved in the T3SS in this strain

(Fig. 5f). However, both the *aceE* and *aceF* strain together with the *ΔpscC* mutant strain elicit

lower interleukin 8 (IL-8) release which is secreted by the epithelial cells, and it is necessary

for the recruitment of the immune system at the site of infection (Fig. 6b). Such reduced

recognition from the epithelial layer of the *aceE* and *aceF* strains might depend on the

secretion of bacterial pyruvate, which is known to mediate the inflammatory response in both

the epithelium and the immune cells [28,29,35]. These results are corroborated by confocal

microscopy data, which show a similar colonization profile on the airway epithelium of the

PAO1 and *aceE* strains, and of the *aceF* and *ΔpscC* respectively. This mechanism of reduced

cellular damage and reduced immunogenicity seems not to depend on the growth defect

associated with the *aceF* strain, since the *ΔpscC* strain shows comparable aggressiveness to

the *aceF* mutant strain but a wild type-like growth rate.

Importantly in our longitudinal collection of clinical strains of *P. aeruginosa*, 20 lineages (clone types in specific pwCF; 89 isolates) harbour mutations in the *aceE* and *aceF* genes and/or additional mutations in T3SS genes. In 9 lineages, PDHc mutations are present alone or anticipate additional T3SS mutations. In 7 lineages, T3SS mutations precede PDHc mutation or both systems are mutated at the same time (4 lineages) already in the first isolate of the lineage (Fig. S7). Altogether these results suggest a role for the *aceE* and *aceF* mutations prior those on the T3SS. Moreover, they provide direct evidence of the contribution of metabolism to bacterial virulence and to the persistence phenotype.

Discussion

Metabolism constitutes a central process which is specifically regulated and optimized according to the nutritional resources available and the phenotypic requirements of the cell. Several studies have shown that metabolic specialization occurs in clinical isolates of *P. aeruginosa* [14]. However, little is known about whether this metabolic specialization is simply an accommodation for other significant fitness gains, or whether it is specifically selected for to enable increased persistence in the host.

By analysing different clinical isolates of *P. aeruginosa*, we show that all infection lineages underwent a substantial metabolic rewiring associated with changes in proteome allocation driven by mutations in metabolic genes. Adapted strains harbouring mutations in the genes encoding the PDHc (*aceE* and *aceF*) are characterized by a chronic-like phenotype (T3SS down-regulation, up-regulation of T6SS, phenazines and alginate biosynthetic pathway and slow growth) suggesting selective advantages in the host [18]. Moreover, adapted strains secrete high amount of pyruvate, which is an important mediator of inflammation in the host [28]. Testing aggressiveness in an ALI culture model confirmed that the *aceE* and *aceF* mutant strains elicit less stimulation of the immune system and reduced epithelial penetration, respectively. Such reduced aggressiveness in the *aceF* mutant strain appears to be mediated by reduced expression of the T3SS effector ExoT, which induces apoptosis in host cells [32,33]. This result is consistent with previous studies showing that mutations in the PDHc-encoding genes leads to repression of T3SS in *P. aeruginosa* [36,37]. Similarly, mutations in the *iso*citrate lyase involved in the glyoxylate shunt in the TCA cycle has also been associated with reduced

T3SS activity proposing a direct correlation of metabolism to virulence [24]. As expected, the DK15 late isolate in our collection shows reduced expression of the *iso*citrate lyase together with suppression of ExoT exotoxin. Importantly, *aceE* and *aceF* mutations mostly precede mutations in the T3SS-encoding genes, indicating a fundamental and broader role of the PDHc mutations during evolution in the host. Moreover, the diversity of *aceE* and *aceF* mutations indicates that the activity of the PDHc can be fine-tuned accordingly to the specific host and consequently lead to different infection outcomes. Indeed, while the *aceE* mutant strain (SNP) shows comparable aggressiveness to PAO1 but reduced recruitment of the immune system (IL-8 secretion), the *aceF* mutant strain (indel) combines the effect of the reduced aggressiveness and that of the reduced immune recruitment.

It is worth noting that pyruvate is a potent scavenger of ROS and, indeed, its use has been suggested as an anti-inflammatory treatment in several diseases [27,35]. Due to the sustained activation of neutrophils and other defects in the homeostatic processes of pulmonary epithelia in CF airways, an abnormal flux of ROS is present which can be alleviated by the bacterial pyruvate secretion [38]. Indeed, it has been shown that treatment of human lung epithelial cells with pyruvate reduces the inflammatory response by reducing the production of IL-8 [39,40], it induces a potent shutdown of the response to LPS in dendritic cells [41], and reduces alveolar tissue destruction in COPD model system [42]. Similarly, inhibition of the PDHc and redirection of the pyruvate flux has been suggested both as a potential anti-inflammation therapy for chronic metabolic diseases [43], and as a cancer treatment [44]. Moreover, fine-tuning of the flux through the mitochondrial PDHc in macrophages and dendritic cells is key for regulating their polarization and thus the balancing between pro- and anti-inflammatory responses [45–47]. LPS-induced polarization of macrophages is prevented by pharmacological inhibition of pyruvate import into the mitochondria [48]. Moreover, flux through the PDHc controls the production of the antibacterial cytokine itaconate [49–52].

The PDHc dysregulation seen in the clinical isolates may, therefore, serve as an alternative mechanism for ensuring active pyruvate secretion and suppression of the immune system by a mechanism of cross-feeding. This mechanism of host-pathogen crosstalk is evolutionary beneficial in persistent infections since ROS produced in the CF airways might select for metabolic specialization in *P. aeruginosa*. Moreover, the consequent reduced activity of the T3SS limits epithelial damage to avoid any further inflammation. These combined

mechanisms can provide a rationale for the broad accumulation and maintenance of PDHc mutations in our collection of *P. aeruginosa* clinical CF isolates and the reduced expression of the PDHc in sputum samples [19,34]. Moreover, it suggests a highly complex and near universal role of the pyruvate node in regulation of both host and pathogen (and their respective functions *in vivo*) through a conserved central metabolite. Such a mechanism might be used years before the development of antibiotic resistance, therefore being of high relevance for the establishment of a chronic phenotype. Understanding specific mechanisms linking metabolism, energy balance and virulence and most importantly how the relationship between the host and the pathogen changes during an infection is of high relevance. Indeed, it could provide new opportunities for improved and more efficient treatment (beyond the classical antibiotic treatment) which are greatly needed.

Methods

Strains and media

The collection of clinical isolates used in this study is a subset of the collection published in Marvig et al., (2015) and Bartell et al., (2019) [19,53]. The local ethics committee at the Capital Region of Denmark (Region Hovedstaden) approved the use of the stored *P. aeruginosa* isolates (registration number H-4-2015-FSP). For information about specific clinical isolates, see Table S1.

For construction of *aceE* and *aceF* mutant strains, derivatives of pACRISPR were constructed with the Uracil Specific Excision Reagent (USER) cloning [54]. The plasmids and primers used are listed in Table S1 and S2 respectively. Target DNA fragments were amplified from gDNA of clinical strains DK12 Late and DK36 Late using the Phusion U polymerase kit (Thermo Fisher Scientific, USA). The resulting PCR products were treated with FastDigest DpnI enzyme (Thermo Fisher Scientific, USA) and ligated with the USER® Enzyme (New England Biolabs, USA). PCR was performed on random *Escherichia coli* DH5alpha colonies using OneTaq® 2X Master Mix (New England Biolabs, USA) to confirm the correct insertions and further sequenced with Sanger method (Eurofins Scientific, Luxembourg). *aceE* and *aceF* mutations in the genome of *P. aeruginosa* PAO1 were introduced using the previously developed CRISPR-Cas9 system [55] and following the indicated protocol [56] with the addition of 0.2%

arabinose in the growth medium during transformation. To confirm the presence of desired

mutations, PCR fragment of the genome around the mutations was amplified and sequenced

with Sanger sequencing (Eurofins Scientific, Luxembourg). To perform confocal microscopy

analyses, strains were tagged with Gfp using four parental mating using a mini Tn7 delivery-

method [57] but with the additional supplementation of 5 mM acetate to ensure growth of

PDHc dysregulated target strains. Transformants were identified by green fluorescence and

validated by comparing growth rate to the untagged target strain.

Bacteria were grown in Synthetic Cystic Fibrosis Media 2 (SCFM2)[58]. To reduce viscosity and

allow for HPLC analysis, DNA and mucins were excluded [59]. Cultures were grown at 37 °C and

250 rpm.

Dynamic exo-metabolomics analyses

Sampling of supernatants was performed in 96-well deep well plates (Cat. No. 0030502302;

Eppendorf, Hamburg, Germany) with an air:liquid ratio of 1:1 using a high-throughput

dilution-based growth method as previously described [60]. Immediately before sampling, OD_{600}

of the cultures were measured in a Synergy^{TM} MX microtiter plate reader (BioTek Instruments

Inc., Winooski, VT, USA). Supernatants were stored at -80 °C until HPLC-analysis. For organic

acids and sugars (glucose, lactate, formate, acetate and pyruvate), a Dionex Ultimate 3000

system (Thermo Scientific,Waltham, United States) with a HPx87H ion exclusion column (125-

0140, Aminex, Dublin, Ireland), equipped with a guard column (125-0129, BioRad, Hercules,

California, United States) and guard column holder (125-0131, BioRad, Hercules, California,

United States) was used. Samples were injected with an injection volume of 20 μL and eluted,

using a 5 mM H_2SO_4 mobile phase, at an isocratic flow of 0.6 mL min^{-1} at 45 °C for 30 min.

Pyruvate was analysed by UV detection at a wavelength of 210 nm, using a System Gold 166

UV-detector (Beckman Coulter, Brea, United States), while the rest of the metabolites were

analysed by RI detection, using a Smartline RI detector 2300 (KNAUER Wissenschaftliche

Geräte, Berlin, Germany). For amino acids (aspartic acid, glutamic acid, serine, histidine,

glycine, threonine, arginine, alanine, tyrosine, valine, phenylalanine, isoleucine, leucine,

lysine and proline), 20 μL of the thawed sample was diluted 1:10 by mixing with 80 μL

Ultrapure MilliQ water and 100 μL of internal standard (20 μg/mL 2-aminobutyric acid and

sarcosine) before injection of 56.5 μL into the instrument. Prior to injection into the column, derivatization of amino acids was performed in the HPLC-instrument by automatic mixing with the following eluents: (i) 0.5% (v/v) 3-mercaptopropionic acid in borate buffer 0.4 M at pH 10.2; (ii) 120 mM iodoacetic acid in 140 mM NaOH; (iii) OPA reagent (10 mg/mL *o*-phtalaldehyde and 3-mercaptopropionic acid in 0.4 M borate buffer); (iv) FMOC reagent (2.5 mg/mL 9-fluorenylmethyl chloroformate in acetonitrile); and (v) buffer A (40 mM Na$_2$HPO$_4$, 0.02% (w/v) NaN$_3$ at pH = 7). Following derivatization, the samples were separated isocratically on a Dionex Ultimater 3000 HPLC with fluorescence detector (Thermo Scientific, Waltham, United States) through a Gemini C18 column (00F-4439-E0, Phenomenex, Værløse, Denmark) equipped with a SecurityGuard Gemini C18 guard column (AJ0-7597, Phenomenex, Værløse, Denmark) with 5 mM H$_2$SO$_4$ at a flowrate of 1 mL min^{-1} at 37 °C for 31 min. Amino acids were detected using an UltiMate™ 3000 Fluorescence variable wavelength UV detector (FLD-3400RS, Waltham, Massachusetts, United States).

Proteomic analyses

To maintain a 1:1 air:liquid ratio, as in the metabolomic analysis, 25 mL SCFM cultures were inoculated from ON cultures in 50 mL Falcon tubes at OD$_{600}$ of 0.05 and then incubated in an orbital shaker at 37 °C and 250 rpm until sampling by centrifugation at mid-exponential phase. Five biological replicates were analysed for PAO1 and the clinical isolates while three biological replicates for the PAO1 derivative strains *aceE* and *aceF* both in presence and absence of 5 mM acetate. Pellets were washed twice with PBS and stored at -80C until protein extraction. For experiment with clinical isolates, protein extraction was done in Lysis buffer A (100 mM Tris, 50 mM NaCl, 1 mM tris(2-carboxyethyl)phosphine (TCEP), 10% glycerol, pH = 7.5) with *cOmplete Mini protease inhibitor* (Roche) by sonication at amplitude 10 for 3x 10s cycles with 20s cooling between, followed by acetone precipitation and resuspension in Lysis buffer B (6 M Guanidinium hydrochloride, 5 mM TCEP, 10 mM chloroacetamide, 100 mM Tris–HCl, pH = 8.5). For experiment with PAO1 derivative mutant strains, protein extraction was done in Lysis buffer B by bead beating with 3-mm zirconium oxide beads at 99 °C for 5 min. in a Tissuelyzer (Retsch, MM 400) at 25 Hz, then boiled, still at 99 °C, in heat block (Eppendorf Thermomixer C) for 10 min. while shaking/mixing at 2000 rpm. In both cases, protein concentrations were determined by micro BCA^{TM} Protein Assay Kit (Thermo Scientific, prod

#23235) and 100 μg protein was used for trypsin digest in Trypsin/Lys-C Buffer (0.1 μg/μL

trypsin, 50 mM Ammonium Bicarbonate). The reaction was stopped by addition of 10 μL 10%

TFA and samples were desalted by stagetipping with C18 filter plugs (Solaμ HRP 2 mg/1 ml 96

well plate, Thermo Scientific). Peptide samples were stored in 40 μL of 0.1% Formic acid at 4

°C until LC-MS analysis.

For the experiment with clinical isolates, LC-MS/MS was carried out using a CapLC system

(Thermo Fisher Scientific Inc., Waltham, USA) coupled to an Orbitrap Q-exactive HF-X mass

spectrometer (Thermo Fisher Scientific Inc., Waltham, USA). The first samples were captured

at a flow of 10 μL/min on a precolumn (μ-pre-column C18 PepMap 100, 5 μm, 100 Å) and then

at a flow of 1.2 μL/min. Peptides were separated on a 15 cm C18 easy spray column (PepMap

RSLC C18 2 μm, 100Å, 150 μmx15cm). The applied gradient went from 4% acetonitrile in water

to 76% over a total of 60 minutes. MS-level scans were performed with Orbitrap resolution

set to 60,000; AGC Target 3.0e6; maximum injection time 50 ms; intensity threshold 5.0e3;

dynamic exclusion 25 sec. Data dependent MS2 selection was performed in Top 20 Speed

mode with HCD collision energy set to 28% (AGC target 1.0e4, maximum injection time 22 ms,

Isolation window 1.2 m/z). For the experiment with the *aceE* and *aceF* mutant strains,

peptides were loaded onto a 2 cm C18 trap column (ThermoFisher 164946), connected in-line

to a 15cm C18 reverse-phase analytical column (Thermo EasySpray ES904) using 100% Buffer

A (0.1% Formic acid in water) at 750bar, using the Thermo EasyLC 1200 HPLC system, and the

column oven operating at 30 °C. Peptides were eluted over a 70 minute gradient ranging from

10% to 60% of 80% acetonitrile, 0.1% formic acid at 250 nL/min, and the Orbitrap Exploris

instrument (Thermo Fisher Scientific) was run in DIA mode with FAIMS Pro^{TM} Interface

(ThermoFisher Scientific) with CV of -45 V. Full MS spectra were collected at a resolution of

120,000, with an AGC target of 300% or maximum injection time set to 'auto' and a scan range

of 400–1000 m/z. The MS2 spectra were obtained in DIA mode in the orbitrap operating at a

resolution of 60.000, with an AGC target 1000% or maximum injection time set to 'auto', and

a normalised HCD collision energy of 32. The isolation window was set to 6 m/z with a 1 m/z

overlap and window placement on. Each DIA experiment covered a range of 200 m/z resulting

in three DIA experiments (400-600 m/z, 600-800 m/z and 800-1000 m/z). Between the DIA

experiments a full MS scan is performed. MS performance was verified for consistency by

running complex cell lysate quality control standards, and chromatography was monitored to check for reproducibility.

Phenotypic characterizations

Growth curves were performed by inoculating 1 μL of ON culture in 149 μL of media, using 96-well microtiter plates (Cat. No. 650001; Greiner Bio-One, Kremsmünster, Austria), covered with plate seals (Ref. 4306311, Thermo Fisher Scientific, United Kingdom) and incubated at 37 °C and 250 rpm in a BioTek ELx808 Absorbance Microtiter Reader (BioTek Instruments Inc., Winooski, VT, USA) for 24 - 48 hours. Antibiotic MICs were determined by microdilution. ON cultures were standardized to OD_{600} = 0.5 and diluted 1:2500 to reach 5×10^5 CFU/mL in fresh SCFM2 media (LB for Azithromycin). Growth assays were performed at increasing antibiotic concentrations and MIC determined based on final OD. Resistance to oxidative stress was measured as the diameter of clearance zones around diffusion disks saturated with 5 μL of fresh 30% H_2O_2 after 24 hours incubation at 37 °C on LB agar plates cast with 3 mL overlay agar containing 100 μL of LB ON culture standardized to OD_{600} = 1. Pyoverdine production was measured as the fluorescence at 400/460 nm excitation/emission on a Synergy H1 Hybrid Multi-Mode Reader (BioTek Instruments, Winooski, VT, USA) of supernatants normalized against OD_{600} of ON cultures in King's B medium. Biofilm formation assay was done as previously described for NUNC peg lids [61] (NUNC cat no. 445497). Motility was measured as the diameter of the motility zone around single colonies deposited in middle layer of 0.3% (swimming), surface layer of 0.6% (swarming) or bottom layer of 1.5% (twitching) LB agar motility plates, after incubation at 37 °C for 24 - 48 hours. For PAO1 wt and *aceEF* mutant strains, pyruvate secretion was determined from supernatants of samples taken after 0, 4, 8 and 24 hours of growth in SCFM2. Supernatants were stored at -80C and analysed by the HPLC method also used for exo-metabolomics.

Infection of ALI cultures

For the Air-Liquid Interface (ALI) infections the BCi-NS1.1 cells were used [62]. Cells were cultured in Pneumacult-Ex Plus medium (STEMCELL Technologies, 05040) supplemented with

Pneumacult-Ex 50x supplement (STEMCELL Technologies, 05008), 96 ng/mL hydrocortisone (STEMCELL Technologies, 07925) and 10 μM Y-27632 ROCK inhibitor (Bio-Techne #1254/10) in a 37 °C, 5% CO_2 humidified incubator. Following expansion, 1.5 x 10^5 cells were seeded onto 6.5-diameter-size transwells with 0.4 μm pore polyester membrane inserts (Corning Incorporated, 3470) previously coated with human type I collagen (Gibco, A1048301). ALI was established once cells reached full confluency by removing media from the apical chamber and replacing media in the basolateral chamber with Pneumacult-ALI maintenance medium (STEMCELL Technologies, 05001). Pneumacult-ALI maintenance medium was supplemented with Pneumacult-ALI 10x supplement (STEMCELL Technologies, 05003), Pneumacult-ALI maintenance supplement (STEMCELL Technologies, 05006), 480 ng/mL hydrocortisone and 4 μg/mL heparin (STEMCELL Technologies, 07980). ALI cultures were grown in a 37 °C, 5% CO_2 humidified incubator for 30 days, with media replacement every 2-3 days. Epithelial polarization was monitored by measurements of the transepithelial electrical resistance (TEER) using a chopstick electrode (STX2; World Precision Instruments). Following 15 days under ALI conditions, the apical surface was washed with PBS every media change to remove accumulated mucus. Biological replicates of bacterial strains were obtained from single colonies on LB agar plates grown ON as precultures in LB and then diluted to an OD_{600} of 0.05 before sampling at mid-exponential phase by centrifugation, washing with PBS and resuspending in PBS at a density of 10^5 CFU/mL. Fully-differentiated BCi-NS1.1 cells were inoculated with 10^3 CFU from the apical side, diluted in 10 μL PBS. Control wells were incubated with bacteria-free PBS. Cells were incubated for 14 hours at 37 °C, followed by addition of 200 μL PBS to the apical side and measurement of the TEER. CFUs were determined by platting 10 μL of 6-fold serial dilutions on LB-agar plates in technical triplicates both for the initial inoculum, as well as for the apical and basolateral solutions following TEER-measurements. The basolateral media was also used for measurements of LDH and IL-8 release in technical triplicates, using the Invitrogen™ CyQUANT™ LDH Cytotoxicity Assay Kit (Invitrogen, C20301) and Human IL-8/CXCL8 DuoSet ELISA Kit (R&D Systems, DY208) according to the manufacturer´s instructions. BCi-NS1.1 cells on transwell inserts were rinsed once with PBS and fixed by adding 4% (wt/vol) paraformaldehyde (PFA) to both apical and basolateral chambers for 20 min at 4 °C. After washing, cells were permeabilized and blocked for 1 hour with a buffer containing 3% BSA, 1% Saponin and 1% Triton X-100 in PBS. Cells were stained on the apical side with Phalloidin-AF488 (Invitrogen, 65-0863-14) and TO-PRO3

(Biolegend, 304008) diluted in a staining buffer (3% BSA and 1% Saponin in PBS) at a 1:500

dilution for 2 hours at room temperature. Transwells were removed from their supports with

a scalpel and mounted on glass slides with VECTASHIELD® Antifade Mounting Medium (VWR,

VECTH-1000). Images were acquired with a Carl Zeiss LSM 510 Confocal Laser Scanning

Microscope (40× magnification, 1.3 oil) and analysed using the ImageJ software.

Data analysis

For genetic analysis, phylogenetic bootstrap consensus tree was constructed by maximum

parsimony analysis using the subtree-pruning-regrafting algorithm and a bootstrap consensus

value of 50% using the software MEGAX [63]. The tree was inferred from concatenated strings

of 8600 positions in the genome containing non-intergenic SNPs relative to PAO1. Enrichment

analyses of functional categories was done using the DAVID Functional Annotation

Bioinformatics Microarray Analysis tool from lists of mutated Locus Tags in each infection

lineage with the reference genome set as *Pseudomonas aeruginosa*. Genomic data are

enclosed in Supplementary Data 1.

For exometabolomics, all chromatograms were analysed and used to construct standard

curves constructed for absolute quantification of concentrations for all 20 metabolites, using

software Chromeleon v7.2.9. All other analysis of exo-metabolomic data was done in JMP Pro

15.0. To compare between different strains and media batch-effects, OD_{600} was normalized

against final OD_{600} of that strain in the experiment and concentrations were normalized

against specific concentrations in SCFM2 controls for each batch. Missing values were

replaced with 20% of lowest value detected for any metabolite in any sample. Principal

component analysis (PCA) and hierarchical cluster analysis (HCA) were done on $C_{metabolite}$ of all

quantified metabolites for 16 samples (8 time-points from biological duplicates) of each

strain. PCA was done on covariance and HCA using Ward's method for cluster analysis.

Metabolite half-life (OD_{50}), defined as the normalized OD_{600}-value, where 50% of the starting

concentration of a metabolite is present, was calculated from the sigmoidal mechanistic

growth model (Equation: $a(1 - bExp(-cx))$ where a = asymptote, b = scale and c = rate).

Metabolomics data are enclosed in Supplementary Data 2.

For the experiment with clinical isolates, proteomic raw files were analysed using Proteome discoverer 2.4 software with the following settings: Fixed modifications: Carbamidomethyl (C) and Variable modifications: oxidation of methionine residues. First search mass tolerance 20 ppm and a MS/MS tolerance of 20 ppm. Trypsin as enzyme and allowing one missed cleavage. FDR was set at 0.1%. The Match between runs window was set to 0.7 min. Quantification was only based on unique peptides and normalization between samples was based on total peptide amount. For the experiment with mutant strains, raw files were analyzed using Spectronaut™ (version 16.2). Dynamic modifications were set as Oxidation (M) and Acetyl on protein N-termini. Cysteine carbamidomethyl was set as a static modification. All results were filtered to a 1% FDR, and protein quantitation done on the MS1 level. The data was normalized by RT dependent local regression model [64] and protein groups were inferred by IDPicker. In both cases, spectra were matched against the *Pseudomonas aeruginosa* PAO1 reference proteome (UniProt Proteome ID UP000002438). In both experiments, any protein that was not quantified in at least 3 of 5 or 2 of 3 biological replicates for all strains were excluded from the analysis. Using JMP Pro 15.0, abundances were normalized by Log_2-transformation and biological replicates used for missing value imputation. PCA Wide was done on correlations and HCA was done using Ward's method for mean Log_2(abundance) and Log_2(Fold change) was calculated for relevant comparisons. Differential expression was determined by two-way ANOVA with Tukey's multiple comparisons test, using GraphPad Prism 9.3.1, and defined as those protein-comparisons where Adjusted P value ≤ 0.05 and Log_2(Fold Change) ≥ |0.6|. Enrichment analysis was done as in the genetic analysis, but with input lists containing Locus Tags of proteins that were differentially expressed, separated into lists of upregulated and downregulated proteins respectively, for each of the relevant strain-comparisons. Proteomics data are enclosed in Supplementary data 3 and 4.

Growth rates and maxOD were calculated in JMP Pro 15.0. Blanks were first subtracted from OD_{600}-measurements and values converted to cm^{-1} (using Greiner dimensions for pathlength). The stationary phase was excluded, and growth rates were calculated by fitting the Exponential 3P model to the exponential phase ($r^2 > 0.99$). Mean ± sd was calculated from biological replicates. GraphPad Prism 9.3.1 was used for statistical analysis of biofilm formation, motility, redox sensitivity, pyoverdine production and MICs (See Figure S5 for details), as well as for ALI infection experiments. ALI data are represented as mean ± SEM.

Replicates represent independent experiments performed with cells from different passages.
Statistical comparisons were calculated using Two-Way ANOVA for TEER and CFU
measurements and One-Way ANOVA for LDH and IL-8 measurements. Statistical significance
was considered for *p*-value < 0.05. All figures were finalized in Adobe Illustrator Artwork 27.0.

Data availability

The authors declare that all data necessary for supporting the findings of this study are
enclosed in this paper (Supplementary Data 1-4). All genomic data is publicly available
through the SRA database and has been published previously by Marvig et al., (2015) [19].

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Author contributions

BHP, SM and RLR designed the project. BHP, FBS and IP performed the experiments and
verified the data. HKJ provided the strains and the clinical data. MW enabled the proteomic
analyses. BHP and RLR wrote the first draft of the paper, which after review by all authors,
was revised according to the co-authors' suggestions. All authors approved the final version
of the manuscript.

Competing interests

The authors declare no competing interests.

Figure 1: Collection of *Pseudomonas aeruginosa* clinical strains. a) Growth rate (hour^{-1}) of early (circles), late (triangles) and PAO1 (square) strains coloured by their clone type. The fold change of growth rate from early to late is shown as bar chart on the right y axis and as number value at the base of each bar. b) The maximal optical density (maxOD) of all isolates, grouped by early *vs* late comparison. Statistical significance was calculated by Unpaired Welch t-test and indicated as *** ($p < 0.001$). c) Growth rate (hour^{-1}) of each strain in M9 minimal media containing 20 mM of a single carbon source glucose (Glu), lactate (Lac) or succinate (Suc). d) Maximum parsimony reconstruction of the analysed strains. The tree is based on 8600 missense and nonsense SNP mutations accumulated during within patient evolution. Branches corresponding to partitions reproduced in less than 50% of bootstrap replicates are collapsed. The percentages of replicate trees in which the associated taxa clustered together in the bootstrap test (500 replicates) are shown next to the branches. e) Distribution of mutations identified in the genome of each infection lineage. Total number of mutations (accumulated or reverted) in the specific lineage is indicated above each bar. f) Enrichment

analysis on mutated genes for KEGG and GO categories. The fold-enrichment is indicated for

each category.

Figure 2: Exo-metabolomics analysis reveals adapted metabotypes. a) PCA showing separation of strains based on their time-resolved exo-metabolomes. Strains are shown as circles (early), triangles (late) and square (PAO1), with dashed arrows indicating most notable trajectories from early to late, coloured by clone type. b) HCA of exo-metabolomics data, showing a general separation between early and late strains. Branches for early isolates are indicated in blue, late isolates in red and PAO1 in black. c) Assimilation hierarchies of the analysed metabolites. Each symbol represents the half-life (OD_{50}) of a specific metabolite while each line connects the same metabolite for each pair of early and late isolates. d) Secretion plots showing variations in concentration of acetate, pyruvate and formate (mM) relative to the normalized growth (OD_{600}). Shaded areas indicate the 95% confidence intervals. e) Table showing the total amount (mM) of carbon sources assimilated for each

661 Figure 3: Proteome composition changes support metabolism specialization. a) PCA showing

662 separation of strains based on their mid-exponential proteomes. Strains are shown as circles

663 (early), triangles (late) and square (PAO1), with dashed arrows indicating most notable

664 trajectories from early to late, coloured by clone type. b) HCA of proteomics data, showing a

general separation between early and late strains. Branches for early isolates are indicated in
blue, late isolates in red and PAO1 in black. c) HCA of differentially expressed proteins within
the COG categories related to metabolism. d) Parallel plots of the number of differentially
expressed (DE) proteins within the COG categories related to metabolism in cluster A (Blue,
shaded) and B (red, transparent). e) Metabolic maps showing the differences between early
clinical strains *vs* PAO1 (left) and late *vs* early clinical strains (right) in pathways related to the
catabolism of nutrients present in SCFM through central carbon metabolism. Arrows
represent individual metabolite-conversions coloured by their pathway. Reactions are
coloured if the underlining enzyme is differentially expressed in more than one clone type –
either with dashed (downregulated) or full (upregulated) lines, or both. Enzymes responsible
for each reaction are indicated by numbered circles. For details on individual enzymes, see
Figure S2. Transporters are shown at the bottom as arrows crossing bacterial cell membrane
with their specific transported metabolites. Asp, Glu and acetate are labelled with * to
indicate that they are represented in two places on the map, due to their involvement in
different parts of central carbon metabolism.

Figure 4: Expression of virulence factors differs in clinical strains *vs* PAO1. a) Enrichment
analysis for KEGG and GO terms by the specific comparisons (Early *vs* PAO1; Late *vs* PAO1;

Late *vs* Early). Icons represent individual lineages and are coloured by fold-enrichment. b)

Differential expression of virulence factors in early clinical strains *vs* PAO1. Only differentially

expressed proteins are represented and are coloured by clone type. c) HCA of differentially

expressed proteins of virulence factors in late *vs* early clinical strains.

Figure 5: *aceE* and *aceF* mutations cause metabolic specialization. a) Schematic of the *aceE*

and *aceF* genes including location and type of mutation found in the DK36 (*aceE*) and DK12

(*aceF*) late strains. b) Growth rate (hour^{-1}) in SCFM2 (blue) and SCFM2 supplemented with 5

mM acetate (red) for PAO1, *aceE* and *aceF* mutant strains, and DK12 and DK36 late clinical

isolates. Bars indicate mean ± SEM, with icons representing biological replicates. Statistical

significance is assessed by two-tailed unpaired parametric Welch t-test and indicated as * (*p*

< 0.05), ** (*p* < 0.01) or **** (*p* < 0.0001). c) Pyruvate secretion (mM) for PAO1 wt (yellow),

aceE (cyan) and *aceF* (magenta) mutant strains over 24 hours. Icons represent biological

replicates. d) PCA and HCA of whole-cell proteomics for PAO1 wt and *aceE* and *aceF* mutant

strains. Filled icons indicate without (-) and unfilled icons indicate with (+) 5 mM acetate. e)

Number of differentially expressed proteins in presence *vs* absence of acetate (purple), for

mutant strain *vs* PAO1, either in absence (orange) or presence (green) of acetate. f) Metabolic

map of enzymes related to pyruvate and acetyl-CoA metabolism for mutant strains *vs* PAO1

in absence (left) or presence (right) of acetate. Reactions are coloured by their pathway if the

underlining enzyme is differentially expressed (dashed if downregulated or continuous if

upregulated). Enzymes responsible for each reaction are indicated by numbered circles. For

details on individual enzymes, see Figure S6. g) Differentially expressed proteins involved in

virulence in *aceE* and *aceF* mutant strains *vs* PAO1 in absence of acetate. Icons indicate

specific proteins that are upregulated (red plus) or downregulated (blue circle).

Figure 6: Aggressiveness of *aceE* and *aceF* strains in Air-Liquid Interface airway infections. a)

Mean ± SEM of Transepithelial Electrical Resistance (TEER) ($\Omega \cdot cm^2$), LDH release and Colony

Forming Units (CFU) in the apical and basolateral ALI compartments after 14 hours of infection

in fully differentiated BCi-NS1.1 cells. b) IL-8 release into the basolateral media indicating

immunogenicity caused by the invading bacteria. Icons represent each biological replicates.
Mock represents un-infected control cells. Statistical significance was determined by Two-
Way ANOVA for TEER and CFU measurements and One-Way ANOVA for LDH and IL-8
measurements and indicated as * ($p < 0.05$), ** ($p < 0.01$), *** ($p < 0.001$) and **** ($p <$
0.0001). c) Confocal images of ALI transwells following infection with *P. aeruginosa* in green
(Gfp), epithelium in red (Phalloidin) and nuclei in blue (To-pro). Scale bar = 40 μm.

Figure S1: a) Number of differentially expressed proteins (top) and Log_2(Fold change) of
individual differentially expressed proteins in late vs. early clinical isolates, separated by
lineage and on the x-axis by COG categories. b) Complete enrichment analysis showing fold-
enrichments separated by comparison and lineage on x-axis and by KEGG and GO terms on y-
axis.

Figure S2: a) Metabolic map in the same style as Fig. 3E for late clinical strains vs PAO1. b)
Table of genes/Locus Tags of all metabolic enzymes included in the map. c-d) Bar charts
showing Log_2(Fold change) of all differentially expressed proteins highlighted on the
metabolic maps. Icons coloured by lineage and separated into three comparisons on x-axis
(Early vs PAO1; Late vs Early; Late vs PAO1). Panel c contains metabolic enzymes and panel d
contains transporters.

Figure S3: a) Hierarchical cluster analysis in the same style as Fig. 4C, showing differential
expression in late vs early clinical strains for several more virulence categories. b) The
Log_2(Fold change) of differentially expressed proteins in late vs early clinical strains separated
into the relevant virulence categories and further separated into the two main clusters from
panel a. Icons are coloured by lineage and lines depict the difference in mean Log_2(Fold
change) between the two clusters.

Figure S4: Schematic of all 18 unique mutations observed for *aceE* (top) and *aceF* (bottom) in

our collection of clinical isolates of *P. aeruginosa*. Grey lines indicate mutation site and letters

indicate nucleotide-sequence coloured by type of mutation.

Figure S5: a) Potential for biofilm formation (surface attachment) of PAO1 wt (blue), as well

as *aceE* (red) and *aceF* (green) mutant strains and DK12 & DK36 late clinical strains after 24

and 48 hours respectively. For the clinical isolates, strain is indicated on the x-axes and

incubation time is indicated as blue (24 hours) and red (48 hours). Attachment is measured

as the ratio of surface-attached cells (OD_{590}) to total number of cells (OD_{600}) after incubation.

For PAO1 wt and *aceE* and *aceF* mutants, all strains were compared by One-Way ANOVA. For

clinical isolates, each strain was compared to itself after 24 and 48 hours of incubation

respectively, using two-tailed unpaired parametric Welch t-test. Significance is indicated as

'ns' ($p > 0.05$), * ($p < 0.05$), ** ($p < 0.01$), *** ($p < 0.001$). Same colouring and statistical analysis

for PAO1 and mutant strains in panel b-d. b) Motility measured as the diameter (mm) of the

zone of growth in motility plates (LB agar). Swimming motility was clearly visible after 24

hours of incubation. Swarming and twitching plates required 48 hours of incubation. c) Redox

sensitivity measured as the diameter of the clearance zone (mm) on bacterial lawns (LB agar)

of each strain from H_2O_2 diffusion disks after 24 hours. d) Pyoverdine production measured

as relative fluorescence (F/OD_{600}) of each strain after 24 hours of growth in King's B medium.

For panel a-d, icons indicate biological replicates and bars represent the mean ± SEM. e) MICs

of PAO1 wt and *aceE* and *aceF* mutant strains. Each cell represents the maxOD of growth

curves under the given condition, following the colour gradient to the right of each heatmap.

The MIC is the concentration where no growth is observed (white). Each heat map shows the

MIC for all three strains for a given antibiotic (Ceftazidime, Meropenem, Piperacillin,

Azithromycin, Chloramphenicol, Ciprofloxacin and Tobramycin). Concentrations (μg/mL)

increase 2-fold downward on the vertical axis and the specific strain is given on the horizontal

axis. Azithromycin MICs were determined in LB, while all other MICs were determined in

SCFM2. Piperacillin was used in combination with the β-lactamase inhibitor Tazobactam.

Figure S6: a) Metabolic map in the same style as Fig. 3E for *aceF* mutant strain vs PAO1

reference in SCFM2 in absence (left) and presence (right) of acetate. b) Parallel plot showing

the number of differentially expressed proteins, separated by metabolic COG categories, in

aceE (cyan) and *aceF* (magenta) mutant strains vs PAO1. c) Enrichment analysis showing fold

enrichment on x-axis separated by KEGG and GO terms on y-axis for *aceE* (left) and *aceF* (right)

mutant strains vs PAO1.

Figure S7: Longitudinal collection of *P. aeruginosa* clinical isolates from CF airways. Icons

indicate isolates carrying mutations in genes encoding PDHc (red squares) and/or T3SS

(purple triangles) proteins, as well as isolates with no mutations in either (grey dots). Isolates

are separated by Clone Type and further separated by patient-specific lineages within Clone

Types (A, B, C). The x-axis shows the length of infection (years) since the first isolate of the

given lineage.

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