Plasmid overlap and evolution between *Enterobacterales* isolates from bloodstream infections and non-human compartments

William Matlock*[,1], Samuel Lipworth*[,1,2], Kevin K. Chau[1], Manal Abu Oun[3], Leanne Barker[1], James Kavanagh[1], Monique Andersson[2], Sarah Oakley[2], Marcus Morgan[2], Derrick W. Crook[1,2,4,5], Daniel S. Read[6], Muna Anjum[3], Liam P. Shaw[#,7]/Nicole Stoesser[#,1,2,4,5], REHAB Consortium

* Contributed equally as first authors

\# Contributed equally as senior authors

[1] Nuffield Department of Medicine, University of Oxford, Oxford, UK

[2] Oxford University Hospitals NHS Foundation Trust, Oxford, UK

[3] Animal and Plant Health Agency, Addlestone, UK

[4] NIHR Health Protection Research Unit in Healthcare Associated Infections and Antimicrobial Resistance at University of Oxford in partnership with Public Health England, Oxford, UK

[5] NIHR Biomedical Research Centre, Oxford, UK

[6] Centre for Ecology and Hydrology, Wallingford, UK

[7] Department of Zoology, University of Oxford, Oxford, UK

Correspondence: William Matlock (william.matlock@ndm.ox.ac.uk) and Nicole Stoesser (nicole.stoesser@ndm.ox.ac.uk)

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Abstract

Horizontal gene transfer in *Enterobacterales* allows mobile genetic elements to move between strains, species, and genera. In particular, the movement of plasmids is a known route for rapid dissemination of antimicrobial resistance (AMR) genes. However, it is difficult to establish to what extent plasmids are shared between *Enterobacterales* causing human infections and those from non-human sources, such as livestock or the environment. While some previous studies have found only limited evidence for genetic overlap, these have often been limited in size, restricted to drug-resistant isolates, and have used fragmented genome assemblies. Here, we report a collection of geographically and temporally restricted isolates from human bloodstream infections (BSI), environmental soils, livestock (cattle, pigs, poultry, sheep), wastewater (influent, effluent), and rivers. Isolates were all collected between 2008-2018 from sampling sites <60km apart. The combined dataset contains 1,458 complete *Enterobacterales* genomes, including 3,697 circularised plasmids of which one third were unclassifiable. We find eight groups of near-identical plasmids seen in both human BSI and non-human isolates, of which two are conjugative F-type plasmids carrying AMR genes. We cluster plasmids based on alignment-free distances and find that 73/247 (30%) plasmid clusters contain plasmids from both human BSI and non-human isolates. Pangenome-style analyses of the 69 most prevalent clusters (1,832/3,697 plasmids) reveals sets of shared core genes alongside accessory gene repertoires. Core-gene phylogenies suggest an intertwined ecology where well-conserved putative plasmid 'backbones' carry diverse accessory functions, potentially linked to niche adaptation. Furthermore, we show that closely related human and non-human plasmids are frequently found across distantly related bacterial hosts. Our findings underline the importance of diverse sampling in 'One Health' approaches for AMR management.

Introduction

Enterobacterales are found both in human compartments (e.g., hospital patients[1–3], healthy individuals[4–6], and wastewater[7,8]) and non-human compartments (e.g., livestock[9–11], waterways[12,13], and soil[9,14]). In recent decades, widespread carriage of antimicrobial resistance (AMR) genes has complicated the treatment of both human and livestock *Enterobacterales* infections[15,16]. The dissemination of AMR genes between *Enterobacterales* occurs in a 'Russian-doll'-style hierarchy of nested, mobilisable genetic structures[17]: genes can not only move between bacterial hosts on mobilisable or conjugative plasmids[18,19] but can also be transferred within and between plasmids and chromosomes by smaller mobile genetic elements (MGEs)[20] such as insertion sequences[19,21,22]. Although this gene movement takes place within plasmids, many plasmids have been shown to have a persistent structure which encodes replication and transfer machinery[23,24] which acts as a stable 'backbone' for diverse accessory gene repertoires, allowing plasmids to be grouped into related taxonomic units[25]. AMR gene dissemination therefore has complex dynamics, similar to other mobilisable genes encoding adaptive functions such as virulence traits[26,27] and heavy metal resistance[28].

Many plasmids can transfer between species and are seen across different niches[29] but the extent to which they are shared between human and non-human compartments remains poorly understood. While previous studies have investigated this topic, they have often been both limited in size given the genetic diversity in these compartments[30,31], and restricted to single species[32] or phenotypes (e.g., drug-resistant isolates[33,34]). Further, fragmented genome assemblies in many cases make recovering complete plasmids, and other MGEs, impossible[35,36]. The conclusion of several studies has been that transmission between human

and non-human compartments (i.e., 'One Health'-associated dissemination) has minimal

relevance to AMR, but this may be driven by sampling strategies. On the other hand, there

are known instances where clinically relevant AMR genes are believed to have emerged from

non-human compartments and subsequently spread within human compartments, stressing

the role of inter-compartmental transfer in AMR gene dissemination (e.g., *mcr-1*[21,37], *bla*CTX-

M alleles[38], and *bla*NDM-1[39]).

To explore *Enterobacterales* plasmid diversity and sharing across compartments in a

geographically and temporally restricted context, we studied hybrid assemblies (see Methods)

of large *Enterobacterales* isolate collections from (i) human bloodstream infections (BSI;

Oxfordshire, UK, 2008-2018), and (ii) livestock (cattle, pigs, poultry, sheep), and waterways

(influent, effluent, and rivers) surrounding wastewater treatment works (WwTWs;

Oxfordshire, 2017).

Results

A large sample of completely reconstructed human and non-human *Enterobacterales*

isolate genomes, including plasmids

We combined genomes from *Enterobacterales* isolates sampled from across Oxfordshire, UK

(Fig. 1a). All sampling sites were both geographically (Fig. 1b) and temporally restricted

(Fig. 1c): all sites <60km apart and sampled between 2008 and 2018. We included *n*=738

sequentially collected human BSI *Enterobacterales* genomes (nosocomial, community, and

other healthcare associated onset), including *n*=1,880 associated plasmids (as previously

described in Lipworth *et al.*, 2021[40]; see Methods). We also included *n*=558 *Enterobacterales*

genomes, including *n*=1,515 plasmids, sampled from livestock faeces (cattle, pig, sheep),

surrounding environmental soils, and wastewater influent and effluent surrounding WwTWs

(as previously described in Shaw *et al.*, 2021[22]; see Methods). In this study, we also

assembled an additional $n=162$ *Enterobacterales* genomes, including $n=302$ plasmids, from

poultry, as well as soils surrounding all livestock farms (see Methods). This resulted in a total

of $n=1,458$ chromosomes and $n=3,697$ plasmids (Table 1), with median 2 plasmids carried

per isolate (IQR=1-4, range=0-16). All genome assemblies included were 'complete': that is,

the chromosome and all plasmids were circularised. Isolates mostly represented the genera

Enterobacterales (see Methods for details of taxonomic assignment): $n=125$ *Citrobacter*

($n=122$ *C. freundii*, $n=2$ *C. sedlakii*, $n=1$ *C. tructae*), $n=1$ *Cronobacter* ($n=1$ *Cronobacter*

sp.), $n=63$ *Enterobacter* ($n=1$ *E. cancerogenus*, $n=62$ *E. cloacae*), $n=1,044$ *Escherichia*

($n=1,044$ *E. coli*), $n=211$ *Klebsiella* ($n=4$ *K. aerogenes*, $n=1$ *K. huaxiensis*, $n=44$ *K. oxytoca*,

$n=163$ *K. pneumoniae*), $n=1$ *Lelliottia* ($n=1$ *L. nimipressuralis*), $n=6$ *Proteus* ($n=4$ *P.*

mirabilis, $n=1$ *P. vulgaris*), and $n=5$ *Salmonella* ($n=5$ *S. enterica*). From the BSI isolates, we

also included $n=2$ *Aeromonas* spp., a non-*Enterobacterales* genus from the wider

Gammaproteobacteria class.

Table 1. Isolate compartment breakdown.			
Compartment	**Sample type(s)**	**No. isolates**	**No. plasmids**
BSI	Community, nosocomial, other healthcare associated infections	738	1,880
Environment	Soil surrounding livestock farms	128	190
Livestock	Cattle faeces	133	215
	Sheep faeces	113	286
	Pig faeces	104	352
	Poultry faeces	34	112
WwTW	Influent/upstream waterways	113	373
	Effluent/downstream waterways	95	289
Total		**1,458**	**3,697**

Table 2. Isolate genus breakdown.						
Compartment	**Isolate genus**					**Total**
	Citrobacter	*Enterobacter*	*Escherichia*	*Klebsiella*	**Other**	
BSI	6	11	547	161	13	**738**
Environment	28	10	85	5	0	**128**
Livestock	26	0	348	9	1	**384**
WwTW	65	42	64	37	0	**208**
Total	**125**	**63**	**1,044**	**212**	**14**	**1,458**

We found a significant association between sampling compartment and isolate genus

(Fisher's test, p-value<5e-4; see Table 2). *Klebsiella* isolates were disproportionately derived

from BSI samples: 76% (161/212) of all *Klebsiella* sequenced were from BSIs, versus 51%

(738/1,458) of all isolates. *Citrobacter* and *Enterobacter* were disproportionately derived

from WwTW samples: 52% (65/125) and 67% (42/63) of sequenced *Citrobacter* and

Enterobacter were from WwTWs samples versus 14% (208/1,458) of all isolates. We

produced chromosomal Mash trees (see Methods) for the two most common isolate species in

the dataset, *E. coli* (72% [1,044/1,458]; see Fig. S1) and *K. pneumoniae* (11% [163/1,458];

see Fig. S2). Both trees demonstrated intermixing of human and non-human isolates within

clades.

One third of plasmids in our dataset are unclassified using conventional methods,

highlighting the extent of plasmid diversity

We contextualised our plasmids within known plasmid diversity using COPLA to determine

each plasmid's 'plasmid taxonomic unit' (PTU; see Methods), which is designed to be

equivalent to a 'species' concept for plasmids[41]. Briefly, COPLA classifies query plasmids

based on average nucleotide identity (ANI) against a non-redundant reference plasmid

database where most plasmids have been assigned to a reference PTU[40]. Within our sample,

64% (2,369/3,697) plasmids were assigned a PTU and 4% (135/3,697) a putative PTU (i.e.,

the query plasmid was clustered with 3 unclassified reference plasmids). This is consistent

with a previous COPLA analysis of 1,000 *Enterobacterales* plasmids which found that 63%

were classified into a PTU[41]. The remaining 32% (1,193/3,697) of plasmids were

unclassified (i.e., connected set with less than 4 plasmids) highlighting the previously

unsampled plasmid diversity within our dataset. In total, we found n=67 known PTUs,

containing a median 9 plasmids (IQR=4-30, range=1-556), where the largest assigned PTU

(556/2,504) was PTU-F$_E$, corresponding to F-type *Escherichia* plasmids[42,43]. The proportion

of unclassified plasmids was higher in environmental/livestock samples (33%; 385/1,155)

versus BSI samples (26%; 485/1,880), emphasising the underrepresentation of non-human

plasmids in reference plasmid databases.

Near-identical plasmid sharing observed between human and non-human

Enterobacterales

We identified instances where a near-identical plasmid was seen in multiple isolates by

grouping plasmids based on a low Mash[44] distance and highly similar lengths (*d*<0.0001 and

longer plasmid ≤1% longer than shorter plasmid; see Methods). For whole genomes, Mash

distance has a strong positive correlation with ANI [45]. We found *n*=225 such near-identical

groups of at least 2 members, covering 19% (712/3,697) plasmids. By bootstrapping *b*=1,000

accumulation curves (ACs) for near-identical plasmids groups and singletons as a function of

the number of isolates, we found a highly 'open' accumulation (Heap's parameter γ=0.97,

Fig. S3) suggesting further isolate sampling would detect more unique plasmids

approximately linearly. Restricting to the BSI or environmental/livestock isolates alone, we

found similar curves for both compartments (Heap's parameters: BSI γ=0.98,

environmental/livestock γ=0.94), suggesting they had similar levels of plasmid diversity.

Near-identical groups containing two plasmids were the most common, representing 71%

(159/225) of groups (group size IQR=2-3, range=2-32). Within near-identical groups,

plasmid length differed by a median 0% (IQR=0-0%, range=0-0.89%), consistent with our

approach incorporating plasmid length as part of clustering. Near-identical groups

represented multiple bacterial host STs (25% [56/225]), species (4% [9/225]), and genera

(4% [9/225]), consistent with plasmids capable of inter-lineage, -species, and -genus transfer.

Further, 15% (34/225) of near-identical groups contained plasmids found in multiple

sampling compartments, indicating inter-compartmental transfer (i.e., 'cross-compartmental

groups'; Fig. 2a). Within cross-compartmental groups, we found $n=4/34$ contained plasmids

found in multiple bacterial species (Fig. 2b), and that most cross-compartmental groups were

made up of conjugative plasmids ($n=16/34$ conjugative, $n=11/34$ mobilisable, $n=7/34$ non-

mobilisable; Fig. 2c). AMR genes were carried in plasmids in $n=13/34$ cross-compartmental

groups (Fig. 2d), with $n=10/13$ of these groups containing plasmids with at least one beta-

lactamase.

As a subset of cross-compartmental groups, we specifically investigated groups that

supported plasmid sharing between human (BSI) and non-human compartments (all

environmental/livestock niches sampled in this study). Plasmids from both human BSI and

environmental/livestock isolates were represented in $n=8/34$ cross-compartmental groups,

comprising $n=45$ plasmids. On investigation of these groups, $n=2/8$ contained non-

mobilisable Col-type plasmids; $n=4/8$ contained mobilisable Col-type plasmids, of which

$n=1/4$ carried the AMR genes *aph(3'')-Ib*, *aph(6)-Id*, *dfrA14*, and *sul2* (see Methods). The

remaining 2/8 groups contained conjugative FIB-type plasmids. One group carried the AMR

genes *aph(3'')-Ib*, *aph(6)-Id*, *bla*TEM-1, *dfrA5*, *sul2*, and the other group carried the MDR

efflux pump protein *robA*.

We attempted to estimate how the number of non-human isolates affected conclusions about

plasmid sharing between human BSI and non-human compartments. We bootstrapped the

number of near-identical BSI plasmid matches against the number of environmental/livestock

isolates sampled ($b=1,000$). The rarefaction curve had an estimated Heap's parameter of

$\gamma=0.95$ (Fig. S4), suggesting many more such cross-compartmental plasmids would be found

with greater sampling. Assuming we sampled only n=100 environmental/livestock isolates

(i.e., around one fifth of our actual sample size of n=512 isolates), we estimated a 39%

(392/1000) chance that we would have detected fewer than 5 matches with BSI plasmids.

Of the plasmids within the near-identical groups, 71% (502/712) were assigned a PTU or

putative PTU. We used homogeneity (h) and completeness (c) to evaluate the relationship

between the groups and non-putative PTUs (see Methods). Briefly, a grouping has h=1 if all

groups only contain a single PTU, and c=1 if all instances of a PTU fall within the same

group[46]. Groups had a perfect completeness (c=1.00) but lower homogeneity (h=0.54),

indicating that our groups contained plasmids from multiple PTUs, but plasmids with the

same PTUs always fell within the same cluster.

Plasmid clustering reveals a diverse population structure

Beyond near-identical groups, which are the strongest suggestion of recent transfer events,

we also wanted to examine the wider population structure of the plasmids. To do this, we

agnostically clustered plasmids based on their genetic content, both because our dataset

contained previously unsampled diversity as seen by the PTU analysis, and because

reference-based classifications such as MOB and replicon typing schemes are known to be

incongruent[47] or unreliable: 16% (602/3,697) of our plasmids had an unidentifiable replicon

type, which is not uncommon[42]. The evolutionary histories of plasmids can incorporate

multiple gain, loss, and rearrangement events in addition to mutations[48], and as such,

traditional measures of genetic relatedness (e.g., single nucleotide variant [SNV] thresholds)

used for genomic epidemiology of whole genomes are likely less appropriate here.

First, we calculated the pairwise plasmid similarities using the Jaccard index (JI) of their 21-

mer content (ranges from 0 to 1, 1 being identical; see Methods). These similarities formed

the edge-weights in a plasmid-plasmid network, which was subsequently thresholded to

sparsify the network and allow the detection of clusters. The threshold was chosen at JI=0.5,

meaning that edges between plasmids with JI<0.5 were deleted from the network. From this

threshold onwards, both the number of connected components and the number of singletons

steadily increased at a similar rate (Fig S5). This regime indicates an approximately stable

non-singleton structure from JI=0.5 onwards.

At this threshold, we detected plasmid clusters using the Louvain algorithm, which optimises

the modularity of the network whilst accounting for plasmid similarities (see Methods).

Plasmid clusters are groups of $n \geq 3$ plasmids that have high within-cluster-similarities and low

between-cluster-similarities. Though non-deterministic, the Louvain algorithm showed low

variation in cluster distribution over 50 runs, consistent with reproducible segregation of

plasmids in clusters (range of clusters detected: 245-247; Fig. S6). We defined n=247

plasmid clusters with a median of 5 plasmid members on average (IQR=3-10, range=3-123)

recruiting 71% (2,627/3,697) of the plasmids. The remainder plasmids were either singletons

(i.e., single, unconnected plasmids; 19% [718/3,697]) or doubletons (i.e., pairs of connected

plasmids; 10% [352/3,697]). By bootstrapping b=1,000 ACs for plasmid clusters, doubletons,

and singletons found against number of isolates sampled (Fig. S7; see Methods), we

estimated that the rarefaction curve had a Heap's parameter γ=0.75, suggesting further isolate

sampling would likely detect more plasmid diversity.

Of the plasmid clusters, n=69/247 plasmid clusters had at least 10 members and covered 50%

(1,832/3,697) of all plasmids (Fig. 3a). We used these prevalent plasmid clusters for

subsequent pangenome-style analyses (see Methods). We found 30% (73/247) of clusters

contained both BSI and environmental/livestock plasmids, representing n=38 unique plasmid

replicon haplotypes (i.e., combinations of replication proteins) of which only 24% (9/38)

were Col-type plasmids, which are often well-conserved and carry few genes[42,49].

Near-identical plasmid groups were also included in the wider cluster analysis, as many were

cross-compartmental and found across bacterial hosts (see earlier, Fig. 2). Of the n=194/225

groups which were clustered, 100% (194/194) had all members fall within the same plasmid

cluster, with n=30/247 clusters containing multiple near-identical plasmid groups. Only 6%

(14/247) of plasmid clusters comprised exclusively of near-identical plasmid groups,

suggesting that near-identical groups of plasmids often have nearby genetically related

plasmids.

Overall, plasmid clusters scored high completeness (c) but low homogeneity (h) with respect

to biological and ecological characteristics (PTU [c=0.99, h=0.66]; replicon haplotype

[c=0.92, h=0.69]; bacterial host ST [c=0.84, h=0.14] in Fig. 3b; predicted mobility [c=0.93,

h=0.20] in Fig 3c). This indicated that characteristics varied between similar plasmids, but

plasmids with the same features usually fell within the same cluster. This is to be anticipated

as replicon haplotypes and mobilities can vary within plasmid families[47], and plasmid

families can have diverse host ranges[29]. Examining the PTU distribution within clusters, most

contained at least one unclassified plasmid (51%; 127/247) or plasmid assigned a putative

PTU (9%; 23/247). However, many clusters exclusively contained just one known PTU

(42%; 105/247).

Plasmids carrying AMR genes were found in 21% (52/247) of the plasmid clusters (i.e.,

'AMR-carrying clusters'), representing $n=550$ plasmids (Fig. 3d). Of the AMR-carrying

clusters, 92% (48/52) contained at least one beta-lactamase-carrying plasmid ($n=437$

plasmids in total). AMR genes were present in a median proportion 67% of AMR-carrying

cluster members (IQR=28-100%, range=3-100%). This highlights that AMR genes are not

necessarily widespread on genetically similar plasmids and can be potentially acquired

multiple different times through the activity of smaller MGEs, such as transposons, or

recombination. For example, cluster 12 was a group of $n=42$ conjugative, PTU-F_E plasmids

found in BSI, wastewater, and waterways. Of these, 31% (13/42) carried the AMR gene

bla_{TEM-1}, and in a range of genetic contexts: $n=9/13$ bla_{TEM-1} genes were found within Tn3 and

$n=4/13$ were carried without a transposase, of which $n=2/4$ were found with the additional

AMR genes $aph(6)-Id$, $aph(3'')-Ib$, and $sul2$. AMR genes were disproportionately carried by

F-type plasmids (61% [337/550] AMR-carrying cluster plasmids versus 34% [891/2627] of

the total clustered plasmids), further underlining their known role in AMR gene

dissemination[43,50,51]. More broadly, bla_{TEM-1} was found in 15% (38/247) of clusters over

$n=292$ plasmids, suggesting a diversity of plasmid backgrounds.

An intertwined ecology of plasmids across human and non-human compartments

Plasmids can change their genetic content, particularly when subject to new selective

pressures[52–54]. There is evidence that the structure of some plasmids can be separated into a

'backbone' of conserved core genes and a 'cargo' of variable accessory genes[23,24]. It is then

possible that cross-compartmental plasmids which have been recently transferred (within

years) could carry the same backbone with minimal mutational evolution but have different

accessory gene content. This could be driven by any of the following: the loss of accessory

genes in the absence of the old niche's selective pressure, the gain of new genes as adaptation

to the new niche, or neutral structural gain/loss as a form of genomic drift.

To investigate the genetic structure of the plasmid clusters, we conducted a pangenome-style

analysis (see Methods). We only considered the n=69/247 plasmid clusters with at least 10

members. For each cluster, we determined a set of core genes (i.e., genes found in ≥95% of

plasmids), alongside an accessory gene repertoire (i.e., genes found in <95% of plasmids).

Within clusters, we found a median 9 core genes (IQR=4-53, range=0-219), and a median 9

accessory genes (IQR=3-145, range=0-801) (Fig. 3e). Core genes comprised a median

proportion 42.2% of the total pangenome sizes (IQR=20.9-66.7%). The median length of

plasmids within a cluster was positively correlated with number of core genes (R=0.85,

t=13.4, p-value<2.2e-16) and total pangenome size (R=0.87, t=14.6, p-value<2.2e-16). At an

individual plasmid level, core genes shared by a cluster comprised a median proportion

62.5% of each plasmid's gene repertoire (IQR=37.4-83.3%; Fig. 3e). Further, putatively

conjugative plasmids carried a significantly higher proportion of accessory genes in their

repertoires than mobilisable or non-mobilisable plasmids (Kruskal-Wallis test [H(2)=193.01,

p-value<2.2e-16] followed by Dunn's test).

Using multiple sequence alignments of the core genes within each cluster, we produced

maximum likelihood phylogenies (see Supp. File 1; see Methods). For this step, we only

considered the n=62/69 clusters where each plasmid had at least 1 core gene. With the

n=27/62 clusters that contained both environmental/livestock and BSI plasmids, we measured

the phylogenetic signal for plasmid sampling compartment using Fritz and Purvis' D[55].

Briefly, if D=1, the distribution of the trait is random with respect to phylogenetic structure

and if D=0, the distribution of the trait is conserved (D can also fall outside this range; see

Methods). We considered the binary 'trait' of human or non-human compartment and

estimated D with n=10,000 permutations. We found 42% (11/26) clusters had D>0.5 (see

Table 3). However, only 23% (6/26) of phylogenies were significantly different (p-

value<0.05) from the conserved null model, compared to 50% (13/26) significantly different

from the random null model. Overall, this indicates that the evolutionary history of plasmid

clusters is neither strictly segregated by sampling compartment nor completely intermixed,

but something intermediate.

Table 3. Fritz and Purvis' D estimates for plasmid phylogenies.			
Cluster	Estimated D	Probability estimated D is significantly different from 1	Probability estimated D is significantly different from 0
2	0.2407	0.0000	0.2256
3	0.6070	0.0060	0.0031
7	0.0073	0.3994	0.3220
9	0.0794	0.0000	0.3421
10	-0.9101	0.1478	0.5357
11	-0.4134	0.0000	0.7482
17	0.5072	0.0175	0.0378
23	0.0045	0.0001	0.4881
24	0.9269	0.3759	0.0074
25	-1.9546	0.3326	0.2656
27	0.4150	0.0994	0.2113
31	-0.1561	0.0035	0.5225
33	2.7016	0.7929	0.1393
34	-1.6007	0.0000	0.9043
35	1.0622	0.5421	0.0319
37	0.9959	0.3749	0.3269
38	0.5876	0.2934	0.2432
39	0.2680	0.0498	0.2827
43	-0.2927	0.0102	0.7268
44	-4.4685	0.0000	0.7459
47	0.0631	0.0488	0.4227
48	2.6723	0.7522	0.0738
52	-0.1550	0.0205	0.5342
55	1.3161	0.5377	0.2235
58	1.4901	0.8494	0.0208
61	1.1262	0.5284	0.0481
64	-3.0852	0.2255	0.7278

Alongside the core gene phylogenies, we generated plasmid cluster gene repertoire heatmaps

(example cluster 2 in Fig. 4a-b; all clusters and heatmaps in Supp. File 1). By visualising the

genes in a consensus synteny order (see Methods), the putative backbone within each plasmid

cluster is shown alongside its accessory gene and transposase repertoire. This highlights how

plasmids might gain and lose accessory functions within a persistent backbone. Log-

transformed linear regression revealed a significant relationship between Jaccard distance of

accessory genes presence against core gene cophenetic distance ($y=0.080\log(x)+0.978$,

$R^2=0.47$, $F(1,52988)=4.75e4$, p-value$< 2.2e$-16; see Fig. S8).

Plasmid evolution between human and non-human compartments is not structured by

bacterial host

We wanted to examine the congruence between the evolution of plasmids within a cluster and

their respective bacterial hosts. Alongside vertical inheritance, conjugative and mobilisable

plasmids are capable of inter-host transference, crossing between bacterial lineages, species,

up to phyla[29]. Bacterial surveillance often tracks clonally evolving lineages[56], including

clinically relevant sequence types such as *E. coli* ST131[57,58] and ST10[59,60], but this might not

account for clinically relevant AMR genes moving on plasmids. Phylogenetic analysis can

determine whether plasmid evolution between human and non-human compartments is driven

by host clonal expansion or by other means of spread.

We chose to inspect plasmid cluster 2, since it was the largest cluster ($n=100$ members) that

contained both human and non-human plasmids. Within cluster 2, all plasmids carried at least

one F-type replicon and were all putatively conjugative, with 75% (75/100) assigned PTU-F$_E$

and 25% (25/100) assigned a putative PTU. Further, 48% (48/100) plasmids carried bla_{TEM-1},

and 51% (51/100) carried more than one AMR gene, so were of clinical significance. All host

chromosomes were *E. coli* except OX-BSI-481_2, which was sequenced from a *S. enterica*

ST 2998 isolate and omitted from the phylogenetic analysis. The *n*=99 E. coli isolates all fell

into one of six phylogroups: A (5/99), B1 (18/99), B2 (52/99), C (14/99), D (7/99), and G

(3/99; see Methods).

Figure 4b-c shows the plasmid core gene phylogeny ($T_{plasmid}$) and the *E. coli* host core gene

phylogeny ($T_{chromosome}$). The *E. coli* phylogeny was structured by six clades corresponding to

the six phylogroups (all had 100% support; see Methods). We found low congruence between

the plasmid core-gene phylogeny and the chromosomal core-gene phylogeny as seen in the

central 'tanglegram' (i.e., lines connecting pairs of plasmid and chromosome tips from the

same isolate). Additionally, we calculated a Robinson-Foulds distance $RF(T_{plasmid},$

$T_{chromosome})$=162, pointing to a high number of structural differences between the phylogenies

(see Methods). Colouring of the tip labels by sampling compartment demonstrated some

evidence of structuring by compartment (*D*=0.24; see earlier).

Within the plasmid phylogeny, we detected a clade of *n*=44 plasmids (support 100%; circled

in grey in Figure 4b) containing both human and non-human plasmids, which were within

median 4 core gene SNPs of each other (IQR=2-8, range=0-59). Placing plasmid evolution at

a rate of one SNP per year (see Methods) we estimated the median time of divergence within

the clade at 4 years prior to sampling, consistent with recent transference between human and

non-human compartments. This plasmid clade was mainly present in phylogroup B2 (20/44),

but also A (3/44), B1 (9/44), C (8/44), and D (4/44), pointing to recent plasmid movement

between bacterial lineages. Further, 77% (34/44) of plasmids within the clade carried *bla*$_{TEM-1}$

(BSI: 25/34, Environmental: 4/34, Livestock: 4/34, WwTW: 1/34), and 82% (36/44) carried

more than one AMR gene, pointing to potential clinical significance.

To examine the evolution of entire plasmid sequences within the clade, we represented all

n=44 plasmids as a 'pangraph'[61] (Figure 4d; see Methods). Briefly, pangraph converts input

sequences into a consensus graph, where each sequence is a path along a set of homologous

sequence alignments i.e., 'blocks', which in series form 'pancontigs'. First, we removed

duplicated blocks from the pangraph. Then, filtering for 'core blocks' (i.e., those found in at

least 95% plasmids), we found 4 pancontigs (40 blocks in total), with the longest at 98,269bp

(total length 125,369bp), indicating a putative plasmid backbone (Fig. 4e). Further, filtering

for 'accessory blocks' (i.e., those found in less than 95% plasmids), we found 18 pancontigs

(39 blocks in total), with median length 2,380bp (total length 63,753bp), forming the

accessory gene repertoire (Fig. 4f). This points to a persistent plasmid backbone structure

with loss/gain events at particular 'hotspots' as well as rearrangements.

Discussion

We have presented a dataset of *Enterobacterales* plasmids sampled from a geographically

and temporally restricted context from both human and non-human compartments. By

analysing this plasmid diversity, our analysis demonstrates how plasmid ecology is

intertwined across compartments, including instances of plasmids carrying genes of clinical

relevance such as AMR genes. Our results suggest the need for broader sampling frames to

fully understand plasmid evolution.

By segregating plasmids into near-identical groups, we detected 8 instances of plasmid

groups likely very recently shared between human and non-human compartments, 3 of which

were MDR plasmids. At first glance, this may seem small. However, accumulation curve

analysis suggested that increasing the size of the dataset would have led to further BSI near-

identical matches at an approximately linear rate. This suggests even a dataset of this size

captures only a small fraction of the true extent of plasmid sharing between human and non-

human compartments. Furthermore, plasmids observed in BSI isolates represent a restricted

and small proportion of human *Enterobacterales* diversity, meaning many more sharing

events may occur in the human gut[62,63] which was only sampled incompletely here using

wastewater influent as a proxy. The human colon contains around 10^{14} bacteria[64], with large

ranges of *Enterobacteriaceae* abundance (in one study, 10^2-10^9 CFU per gram of stool[65]).

Detailed study of within-niche diversity suggest that these populations can be highly diverse

and fluctuate over short periods of time[66]. Even if the proportion of plasmids which are

shared appears small, it may still be epidemiologically important particularly given known

examples of clinically relevant AMR genes emerging from non-human compartments into

human compartments. Future studies need to carefully consider the limitations of sampling

frames in detecting any genetic overlap, given both substantial diversity and the effects of

niche and geography[22,31].

To capture broader evidence of ecological overlap of plasmids between compartments, we

grouped plasmids based on their *k*-mer content into plasmid clusters, finding that just under

one third (73/247) of these plasmid clusters were present in both human and non-human

compartments. Over one fifth (52/247) of plasmid clusters contained plasmids carrying AMR

genes, totalling 550 plasmids. Most (48/52) of these 'AMR-carrying clusters' contained at

least one beta-lactamase producing plasmid. Further, within AMR-carrying clusters, AMR

genes were carried by a median proportion of two thirds (67%) of member plasmids. This

underlines that plasmid surveillance should focus on both AMR carrying-plasmids and their

close genetic relatives, in part due to transposon-mediated spread of AMR genes.

Using a pangenome-style analysis on plasmid clusters, we showed that plasmids within a

cluster can share sets of near-identical core genes alongside diverse accessory gene

repertoires. Building phylogenies from alignments of core genes, we demonstrated that

plasmids with more distantly related core genes tended to have dissimilar accessory gene

content. In contrast, plasmids with more closely related core genes can have a wide range of

accessory gene content. This suggests how persistent 'backbone' structures might gain and

lose accessory functions during recent evolutionary history (on timescales of years), across

human and non-human compartments. This analysis should motivate the need for

evolutionary models for plasmids which can accommodate well-conserved backbone

evolution alongside accessory structural changes and gain/loss events. However, estimating

appropriate rates is a challenge. We assumed that plasmids with a few SNPs in their core

'backbones' were likely to have common ancestors on timescales of years, but little is known

about appropriate values for mutation rates in plasmids and even less for non-mutational

processes such as gene gain and loss. By examining plasmid relatedness compared to that of

their bacterial hosts, we also demonstrated that cross-compartmental plasmid spread is not

driven by clonal lineages.

Our study had several limitations. Our non-human isolates were not as temporally varied as

the BSI isolates, meaning we could not fully explore linked temporal evolution. Isolate-based

methodologies are incomplete and biased approaches to evaluating the true diversity of these

compartments; complete or targeted metagenomic approaches would be appropriate for future

studies. Further, the 'origin' location of an isolate is poorly defined for wastewater and river

isolates. WwTWs agglomerate multiple sources together, so they were not included when

evaluating the similarities between BSI and environmental/livestock plasmids. We only

analysed plasmids from complete genomes i.e., where the chromosome and all plasmids were

circularised, meaning we disregarded proportions of the BSI dataset, REHAB dataset, and

new poultry/soil assemblies (approximately 23%, 33%, and 34% of isolates, respectively).

We have focused only on plasmids as horizontally transmissible elements here; detailed study

of other smaller mobile genetic elements across-compartments would represent interesting

future work. We have also investigated *Enterobacterales*: however, plasmid sharing is also

known to occur between *Enterobacterales* and other bacterial families and would have been

missed by this study. Lastly, our isolate culture methods for REHAB may not have been as

sensitive for the identification of *Klebsiella* spp. as for other *Enterobacterales* such as

Escherichia, as we used chromogenic agars designed to identify multiple *Enterobacterales*

genera and did not use enrichment and selective culture on Simmons citrate agar with

inositol[67].

In conclusion, this study presents to our knowledge the first large-scale geographically and

temporally restricted analysis of *Enterobacterales* plasmid overlap between human and non-

human compartments. Although we found few instances of near-identical plasmids present

across these compartments, we do not believe this should be interpreted as conclusive

evidence that human and non-human compartments have distinct and separate plasmid

evolution. Considering the broader evolutionary dynamics of plasmids, the epidemic spread

of a fixed and unchanging plasmid – whether vertically within a clonal host or horizontally

between hosts – is only one mechanism by which AMR genes can spread. Indeed, by

clustering plasmids, we have shown instances of plasmids between compartments which are

highly related in their core 'backbone', suggestive of recent shared ancestry, but diverse in

their accessory gene content including AMR genes. This would be consistent with an

intertwined ecology of plasmids across human and non-human compartments, where putative

'backbone' plasmid structures can rapidly gain and lose accessory genes following cross-

compartmental spread. Without broad sampling strategies, future One Health studies may

remain unable to explore this aspect of plasmid evolution – an aspect which involves not

merely the 'numerator' of AMR-carrying plasmids but also a much larger 'denominator' of

related plasmid diversity.

Methods

BSI isolates

Human BSI *Enterobacterales* isolates (nosocomial, community, and other healthcare

associated onset) were sampled from patients presenting to $n=4$ hospitals within Oxfordshire,

UK, from September 2008 to December 2018 (as previously described in Lipworth *et al.*,

2021[40]). Although all patients were sampled in Oxfordshire, a total of $n=505/738$ patients

originated from Oxfordshire postcodes, $n=133/738$ from surrounding counties, and

$n=100/738$ had location information omitted. This study aimed to capture overall plasmid

diversity as well as locally important MDR outbreak plasmids; therefore, assemblies which

were not complete ($n=215/953$ total assembled) i.e., chromosome and all plasmids

circularised, were omitted.

REHAB Isolates

Enterobacterales isolates from the REHAB project sampled faeces and nearby environmental

soils from $n=14$ farms ($n=5$ cattle, $n=4$ pig, $n=5$ sheep), and wastewater influent and effluent

surrounding $n=5$ WwTWs, across 3 seasonal timepoints in 2017 (as previously described in

Shaw *et al.*, 2021[22]). Assemblies which were not complete ($n=269/827$ total assembled) i.e.,

chromosome and all plasmids circularised, were omitted.

Additional poultry and environmental soil isolates

An additional $n=247$ environmental soil and poultry *Enterobacterales* isolates were

assembled for this study, originally collected for the REHAB project[22] from within and

nearby $n=5$ poultry farms. DNA extraction and sequencing was performed as in Shaw *et al.*,

2021[22]). From these, $n=162/247$ complete assemblies were reconstructed (plasmids and

chromosomes). Genomes were hybrid assemblies, using Illumina 150bp paired-end short

reads and Oxford Nanopore/PacBio long reads, and were recovered using Unicycler[68] (v.

0.4.9; default hybrid assembly parameters except min_component_size 500 and --

min_dead_end_size 500). Briefly, Unicycler produces a short read assembly graph using

SPAdes[69], then bridges the gaps with miniasm[70] and Racon[71]. Finally, assemblies are

polished with Pilon[72] using alignments of the short reads.

Taxonomic assignment

Chromosome sequence types (STs) were determined with mlst[73] (v. 2.19.0), which makes use

of the PubMLST database[74]. For the $n=11/1,458$ chromosomes which could not be typed with

mlst, species were determined with the PubMLST 'species ID' web-tool[75], for which all had a

support=100, except for *L. nimipressuralis* which had support=83. Of these, $n=5/11$ were

from BSI, $n=4/11$ from livestock, and $n=2/11$ from effluent/downstream of WwTWs. Of the

plasmids found in these isolates, only OX-BSI-707_4, from a *Proteus mirabilis* isolate, was

clustered in cluster 6, and OX-WTW-105_2, from a *Klebsiella huaxiensis* isolate, was

clustered in cluster 115.

Chromosome trees

Trees for *E. coli* and *K. pnemoniae* chromosomes were produced using Mashtree[76] on

'accurate' mode (--mindepth 0 --numcpus 12).

PTU classification

Plasmids were assigned a plasmid taxonomic unit (PTU) using COPLA[41] (default parameters

except -t circular, -k Bacteria, -p Pseudomonadota, -c Gammaproteobacteria, and

-o Enterobacterales), based on the classification system developed in Redondo-Salvo *et al.*,

2021[29]. COPLA compares query plasmids to a database of PTU reference plasmids, assigning

a PTU when both (i) the ANI>0.7 along 50% of the length of the smallest plasmid in the

comparison, and (ii) a graph-neighbouring condition to existing PTU clusters is satisfied. The

COPLA reference database contains over 10,000 curated, non-redundant plasmids retrieved

from the 84th NCBI RefSeq database in 2017[77].

526 Plasmid annotation

All plasmids were annotated with Prokka[78][80] (v. 1.14.5) with default parameters. For replicon

typing, Abricate[79] (v. 1.0.0) was used with the PlasmidFinder[80], ISfinder[81], and BacMet[82]

databases with default parameters and output filtered for 80% minimum coverage. For

annotating AMR genes, NCBI Antimicrobial Resistance Gene Finder (AMRFinderPlus)[83] (v.

3.10.18) was used with default parameters. For putative plasmid mobilities, we used MOB-

typer from MOB-suite[84] (v. 3.03) with default parameters, which predicts mobility based on

annotations of MOB-typer predicts mobility based on of annotations of relaxase (*mob*),

mating pair formation (MPF) complex, and *oriT* genes. Briefly, a plasmid is putatively

labelled conjugative if it has both relaxase and MPF, mobilisable if it has either relaxase

or *oriT* but no MPF, and non-mobilisable if it has no relaxase and *oriT*.

537 Near-identical plasmid screening

Groups of near-identical plasmids were detected as connected components in a plasmid-

plasmid network with Mash distance[44] (v. 2.3; default parameters except sketch size -s

1000000) weighted edges, at a threshold $d<0.0001$. Briefly, Mash distance estimates an

evolutionary distance on a reduced-length MinHash sketch of the sequences. Since Mash is a

probabilistic estimate of evolutionary distance, we confirmed the probability of seeing any of

our pairwise Mash distances in the near-identical groups by chance was 0. We required the

shortest plasmid to be within 1% length (bp) of the longest plasmid, to account for assembly

errors. Network analysis was performed using the igraph[85] library (v. 1.2.7) in R.

546 Accumulation and rarefaction curves

To generate an accumulation curve, isolates were sampled without replacement in a random

order. For each isolate, the new plasmid diversity was recorded. For Fig. S3, we recorded the

number of new near-identical plasmid groups and singletons. For Fig. S4, we recorded the

number of near-identical matches with BSI plasmids from only environmental/livestock

isolates. For Fig. S7, we recorded the number of new clusters, doubletons, and singletons. A

bootstrapped average of $b=1,000$ accumulation curves was plotted for the rarefaction curve.

The bootstraps were also used to estimate Heap's parameter (γ) by fitting a linear regression

to log-log transformed data. For $\gamma<0$, it is possible to sample the entire diversity, and for

$1>\gamma>0$, the diversity will increase with every additional sample[86].

Plasmid similarity

Plasmid Jaccard index (*JI*) was calculated using Mash[44] (v. X; default parameters except

sketch size -s 1000000). The Jaccard index (*JI*), given by

$$JI(A, B) = \frac{|A \cap B|}{|A \cap B|}$$

where *A*, *B* are the sets of *k*-mers of plasmids *a*, *b*, respectively. This measures extent of *k*-

mer sharing between plasmids, range=0-1, where 1 indicates an identical *k*-mer repertoire.

Since the sketch size was larger than the plasmid lengths (except for one plasmid in the

dataset, OX-ENV-67_2, which was larger than 1Mbp at 1,310,597bp and was not clustered;

the next smallest was OX-WTW-80_2 at 394,284bp), the calculated Jaccard indices were

almost always exact.

Plasmid network and clustering

The determination of the plasmid-plasmid network, threshold, and clusters could be achieved

with several alternative methodologies. Plasmid networks have previously been constructed

by full sequence alignments[87], annotated genes[88], and alignment-free Mash distances[43,89,90].

We chose to use the Jaccard index of entire plasmid *21*-mer distributions to capture coding

sequences, their immediate contexts[91,92], and intergenic regions[93,94], all of which have known

importance to bacterial evolution. Network thresholding to some extent depends subjectively

on the dataset, with trade-offs between successfully revealing the underlying structure of

plasmid relationships without excessively separating relatives. We chose a data-driven

threshold as adopted by Ledda *et al.*, 2018[88] for their plasmid network, which examined the

evolution of connected components within the network. This ensured the threshold was

chosen where the regime of connected component evolution approximately stabilises,

minimising excessive network breakup. Plasmid clusters were then detected with the Louvain

algorithm which optimises the network modularity by iterative expectation-maximisation[95].

This aims to maximise the density of edges within clusters against edges between clusters.

The algorithm was implemented using the python-louvain (v. 0.16) Python module. Although

the algorithm is non-deterministic, multiple runs demonstrated minimal variation at our

chosen network threshold. Overall, these approaches add to the growing literature describing

suitable methodologies for clustering plasmids.

Cluster homogeneity and completeness

Homogeneity (h) and completeness (c) are dual conditional entropy-based measures,

independent of cluster and metadata label distributions[46]. A clustering satisfies homogeneity

($h =1$) if all cluster members have the same metadata label-type. Consider a network with N

nodes, partitioned by a set of metadata labels, $M = \{m_i | i = 1, ..., n\}$, and a set of

communities, $C = \{c_j | j = 1, ..., m\}$. Let $A = \{a_{ij}\}$ represent the ij^{th} entry in the contingency

table of partitions. Hence, a_{ij} counts the number of nodes with label m_i in community c_j. We

then say

$$h = \begin{cases} 1 & \text{if } H(M, C) = 0 \\ 1 - \dfrac{H(M \mid C)}{H(M)} & \text{else} \end{cases}$$

594   where

$$H(M \mid C) = - \sum_{c=1}^{|C|} \sum_{m=1}^{|M|} \frac{a_{mc}}{N} \log \frac{a_{mc}}{\sum_{c=1}^{|M|} a_{mc}}$$

596   and

$$H(M) = - \sum_{m=1}^{|M|} \frac{\sum_{c=1}^{|C|} a_{mc}}{n} \log \frac{\sum_{c=1}^{|C|} a_{mc}}{n}$$

598   are the conditional entropy of the metadata given the clusters and the entropy of the clusters,

599   respectively $H(M|C) = 0$ when the cluster partition coincides with the metadata partition,

600   and no new information is added. A cluster partition satisfies completeness (c =1) if all

601   instances of a metadata label-type are assigned the same cluster. Completeness is defined

602   dually by

$$c = \begin{cases} 1 & \text{if } H(C, M) = 0 \\ 1 - \dfrac{H(C \mid M)}{H(C)} & \text{else} \end{cases}$$

The measures were calculated using the clver library (v. 0.1.1) in R.

Cluster pangenome analysis

Cluster pangenomes were generated using Panaroo[96] (v. 1.2.9) with parameters default except

--clean-mode sensitive, --aligner mafft, -a core, and --core_threshold 0.95. For core gene

alignments, the threshold was set at minimum 95% presence amongst clustered plasmids,

whereby they were aligned using MAFFT[97] (v. 7.407) with default parameters. An identical

approach was taken for the host chromosome phylogeny in Figure 4.

Plasmid core gene phylogenies

Maximum likelihood core-gene phylogenies were generated using IQ-Tree[98] (v. 2.0.6) with

parameters -m GTR+F+I+G4 -keep-ident -T 2 -B 1000. The substitution model used was

general time reversible (GTR) using empirical base frequencies form the alignment (F),

allowing for invariable sites (I) and variable rates of substitution (G4). We used n=1000

ultrafast bootstraps (B 1000; see Minh *et al.*, 2013[99]) to visually inspect larger clades for

support. Briefly, 95% support approximates a 95% probability that the clade is genuine. Only

the n=62/69 clusters (excluding 6, 8, 26,2 9,3 2, 40, and 65) where every plasmid carried at

least 1 core gene were analysed. Phylogenies were primarily plotted using the R library

ggtree[100].

Fritz and Purvis' *D*

Fritz and Purvis' *D* measures phylogenetic signal for binary traits[55]. First, we calculate the

character state changes required to observe our phylogeny (d_{obs}). To account for phylogeny

size and prevalence, d_{obs} is standardised under the two null models (i) tip labels are random

permuted (d_r), and (ii) tip labels are distributed under the expectation of a Brownian motion

model of evolution (d_b). Then, we define

$$D = (d_{obs} - \overline{d_b})/(\overline{d_r} - \overline{d_b}).$$

Hence, for $D \approx 1$, d_{obs} follows d_r more closely, and for $D \approx 0$, d_{obs} follows d_b more closely. We

calculated d_{obs} n=10,000 times and averaged the result, as well as calculate *p*-values for

significant deviation from d_r or d_b. *D* was implemented using the R library caper[101]. Fritz and

Purvis' *D* is normally used for cross-species analysis so is not benchmarked for plasmids.

Results for phylogenies with less than 25 tips should be viewed more conservatively due to

reduced statistical power in these instances.

Consensus gene synteny heatmaps

For each cluster, we first generated a list of every possible pair of genes in the pangenome.

Then for each plasmid, we counted the distance between these pairs, modulo the number of

genes in the plasmid. If a gene was absent in a plasmid, NA was used. We then calculated the

median of these values across all plasmids in the cluster. We then built a dendrogram from a

hierarchal clustering of the median distances. The order of the tip labels in the dendrogram

were then used as the 'consensus gene synteny'.

Accessory gene distances

Plasmid accessory gene distances were calculated using pairwise Jaccard distances on gene

presence-absences matrices. For plotting the cluster-wise plasmid core gene cophenetic

distance against accessory gene presence-absence Jaccard distance, only the $n=26/62$ clusters

with at least 50 accessory genes were plotted.

Chromosome core gene phylogeny

An identical approach was taken to the plasmid phylogenies. *E. coli* phylogroups were typed

using EzClermont[102] (v. 0.7.0) with default parameters. Robinson-Foulds distance was

calculated using the R library phangorn[103].

Plasmid mutation rate

Mutation rates per base pair in microbes typically arise from DNA replication and tend to be

below $m=10^{-9}$ per site per generation[104] or perhaps as low as 10^{-10} per site per

generation[105,106]. For a plasmid of size L, one therefore expects L x m mutations per plasmid

per generation. For example, if the plasmid has $L=10^5$ then in each generation 1 in 10,000

plasmids will gain a mutation. The generation time of *E. coli* per day in the human gut has

been estimated to be between 6 and 20 generations per day[107]. For large plasmids that exist at

a copy number of ~1, the plasmid generation time is the cell generation time. More generally,

for a plasmid copy number p the number of replications of the plasmid expected for a given

number of cell generations g will be p x g (assuming that plasmid copies are simply and

linearly related to the realised number of replications per cell). A crude estimate for the

expected mutation rate per time period for a plasmid is therefore given by L x m x p x g. For a

plasmid of $L=100$ kbp and $p=1$, assuming $m=[0.1\text{-}1]\text{x}10^{-9}$ per site per generation and $g=[6\text{-}$

$20]\text{x}365$ per year, one would expect it to accumulate ~0.5 mutations a year (between ~0.02-

0.7 depending on assumptions). One obtains the same result for $L=10$ kbp and $p=10$. There is

a strong inverse correlation between plasmid size and copy number. This suggests that a

suitable upper bound for the expected number of mutations for a typical plasmid per year

(under neutral evolution) is of the order of magnitude of 1 SNP a year. This rough 'SNPs and

years' rule-of-thumb appears consistent with known empirical results. For example: 100kbp

I1-type *Shigella* plasmids isolated between 2007-2010 in Vietnam were separated by at most

2 SNPs[108]; 30kbp X4-type plasmids carrying *mcr-1* isolated between 2016-2018 in China

were separated by most 4 SNPs[34] (analysis not shown).

Pangraph analysis

673 We used pangraph (v. 0.5.0) to build a pangraph of the clade within plasmid cluster 2, using

674 the --circular flag and otherwise default parameters. We used pangraph export (--edge-

675 minimum length 0, default parameters) to export the graph to GFA format and then visualised

676 this using Bandage[109].

Data visualisation

678 Plots were primally produced using the R library ggplot2[110], with additional graphics in

679 BioRender[111].

Data availability

681 Study metadata is provided in Table S1. Accessions for poultry and environmental soil isolate

682 reads are given in Table S2, and assemblies will shortly be made available on NCBI.

683 Accessions for existing BSI and REHAB reads and assemblies can be found in Lipworth *et*

684 *al.*, 2021[40] and Shaw *et al.*, 2021[22], respectively.

Code availability

686 Analysis scripts can be found in the GitHub repository

687 https://github.com/wtmatlock/oxfordshire-overlap.

REHAB Consortium.

689 Manal AbuOun[2], Muna F. Anjum[2], Mark J. Bailey[3], Brett H[8], Mike J. Bowes[3], Kevin K.

690 Chau[1], Derrick W. Crook[1,6,7], Nicola de Maio[1], Nicholas Duggett[2], Daniel J. Wilson[1,9],

691 Daniel Gilson[2], H. Soon Gweon[3,4], Alasdair Hubbard[10], Sarah J. Hoosdally[1], William

Matlock[1], James Kavanagh[1], Hannah Jones[2], Timothy E. A. Peto[1,6,7], Daniel S. Read[3], Robert

Sebra[5], Liam P. Shaw[1], Anna E. Sheppard[1,6], Richard P. Smith[2], Emma Stubberfield[2], Nicole

Stoesser[1,6,7], Jeremy Swann[1], A. Sarah Walker[1,6,7], Neil Woodford[11]

[1] Nuffield Department of Medicine, University of Oxford, Oxford, UK

[2] Animal and Plant Health Agency, Weybridge, Addlestone, UK

[3] UK Centre for Ecology & Hydrology, Wallingford, UK

[4] University of Reading, Reading, UK

[5] Icahn Institute of Data Science and Genomic Technology, Mt Sinai, NY, USA

[6] NIHR HPRU in healthcare-associated infection and antimicrobial resistance, University of Oxford, Oxford, UK

[7] NIHR Oxford Biomedical Research Centre, University of Oxford, Oxford, UK

[8] Thames Water Utilities, Clearwater Court, Vastern Road, Reading, UK

[9] Wellcome Trust Centre for Human Genetics, University of Oxford, Roosevelt Drive, Oxford, UK

[10] Department of Tropical Disease Biology, Liverpool School of Tropical Medicine, Liverpool, UK

[11] Antimicrobial Resistance and Healthcare Associated Infections (AMRHAI) Reference Unit, National Infection Service, Public Health England, London, United Kingdom

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Bibliography

1.   Linh, T. D. *et al.* Expansion of KPC-producing Enterobacterales in four large hospitals

in Hanoi, Vietnam. *Journal of Global Antimicrobial Resistance* **27**, (2021).

2.   Rivera-izquierdo, M. *et al.* Oxa-48 carbapenemase-producing enterobacterales in

spanish hospitals: An updated comprehensive review on a rising antimicrobial

resistance. *Antibiotics* vol. 10 (2021).

3.   Kraftova, L. *et al.* Evidence of an epidemic spread of KPC-producing Enterobacterales

in Czech hospitals. *Scientific Reports* **11**, (2021).

4.   Onduru, O. G., Mkakosya, R. S., Rumisha, S. F. & Aboud, S. Carriage prevalence of

extended-spectrum β-lactamase producing enterobacterales in outpatients attending

community health centers in Blantyre, Malawi. *Tropical Medicine and Infectious*

Disease **6**, (2021).

5.   Fröding, I., Valik, J. K., Bolinder, L., Nauclér, P. & Giske, C. G. Prediction of

bloodstream infection caused by extended-spectrum β-lactamase-producing

Enterobacterales in patients with suspected community-onset sepsis. *International*

Journal of Antimicrobial Agents **53**, (2019).

6.   Weinstein, E. J. *et al.* A clinical prediction tool for extended-spectrum cephalosporin

resistance in community-onset enterobacterales urinary tract infection. *Open Forum*

Infectious Diseases **6**, (2019).

7.   Asaduzzaman, M. Environmental transmission of antibiotic resistant bacteria through

waste water run-off in Bangladesh. *International Journal of Infectious Diseases* **101**,

82 (2020).

8.   Cahill, N. *et al.* Hospital effluent: A reservoir for carbapenemase-producing

Enterobacterales? *Science of the Total Environment* **672**, (2019).

9.   Subramanya, S. H. *et al.* Detection and characterization of ESBL-producing

754   Enterobacteriaceae from the gut of subsistence farmers, their livestock, and

755   the surrounding environment in rural Nepal. *Scientific Reports* **11**, (2021).

756   10.   Abuoun, M. *et al.* A genomic epidemiological study shows that prevalence of

757   antimicrobial resistance in enterobacterales is associated with the livestock host, as

758   well as antimicrobial usage. *Microbial Genomics* **7**, (2021).

759   11.   Fournier, C., Aires-de-Sousa, M., Nordmann, P. & Poirel, L. Occurrence of CTX-M-

760   15- and MCR-1-producing Enterobacterales in pigs in Portugal: Evidence of direct

761   links with antibiotic selective pressure. *International Journal of Antimicrobial Agents*

762   **55**, (2020).

763   12.   Lazăr, V. *et al.* Antibiotic resistance profiles in cultivable microbiota isolated from

764   some romanian natural fishery lakes included in Natura 2000 network. *BMC*

765   *Veterinary Research* **17**, (2021).

766   13.   Díaz-Gavidia, C. *et al.* Isolation of Ciprofloxacin and Ceftazidime-Resistant

767   Enterobacterales From Vegetables and River Water Is Strongly Associated With the

768   Season and the Sample Type. *Frontiers in Microbiology* **12**, (2021).

769   14.   Koutsoumanis, K. *et al.* Role played by the environment in the emergence and spread

770   of antimicrobial resistance (AMR) through the food chain. *EFSA Journal* **19**, (2021).

771   15.   Buchy, P. *et al.* Impact of vaccines on antimicrobial resistance. *International Journal*

772   *of Infectious Diseases* vol. 90 (2020).

773   16.   Ruppé, E. *et al.* From genotype to antibiotic susceptibility phenotype in the order

774   Enterobacterales: a clinical perspective. *Clinical Microbiology and Infection* **26**,

775   (2020).

776   17.   Sheppard, A. E. *et al.* Nested Russian doll-like genetic mobility drives rapid

777   dissemination of the carbapenem resistance gene blakpc. *Antimicrobial Agents and*

778   *Chemotherapy* **60**, (2016).

779   18.   Madec, J. Y. & Haenni, M. Antimicrobial resistance plasmid reservoir in food and

780   food-producing animals. *Plasmid* vol. 99 (2018).

781   19.   Che, Y. *et al.* Conjugative plasmids interact with insertion sequences to shape the

782   horizontal transfer of antimicrobial resistance genes. *Proc Natl Acad Sci U S A* **118**,

783   (2021).

784   20.   Leekitcharoenphon, P. *et al.* Genomic evolution of antimicrobial resistance in

785   Escherichia coli. *Scientific Reports* **11**, (2021).

786   21.   Wang, R. *et al.* The global distribution and spread of the mobilized colistin resistance

787   gene mcr-1. *Nat Commun* **9**, 1–9 (2018).

788   22.   Shaw, L. P. *et al.* Niche and local geography shape the pangenome of wastewater-and

789   livestock-associated Enterobacteriaceae. *Science Advances* **7**, (2021).

790   23.   Orlek, A. *et al.* Plasmid classification in an era of whole-genome sequencing:

791   Application in studies of antibiotic resistance epidemiology. *Frontiers in Microbiology*

792   vol. 8 (2017).

793   24.   Norberg, P., Bergström, M., Jethava, V., Dubhashi, D. & Hermansson, M. The IncP-1

794   plasmid backbone adapts to different host bacterial species and evolves through

795   homologous recombination. *Nature Communications* **2**, (2011).

796   25.   Garcillán-Barcia, M. P., Alvarado, A. & de la Cruz, F. Identification of bacterial

797   plasmids based on mobility and plasmid population biology. *FEMS Microbiology*

798   *Reviews* vol. 35 (2011).

799   26.   Mairi, A. *et al.* OXA-48-producing Enterobacterales in different ecological niches in

800   Algeria: Clonal expansion, plasmid characteristics and virulence traits. *Journal of*

801   *Antimicrobial Chemotherapy* **74**, (2019).

802   27.   Amaretti, A. *et al.* Antibiotic resistance, virulence factors, phenotyping, and

803   genotyping of non–escherichia coli enterobacterales from the gut microbiota of healthy

804   subjects. *International Journal of Molecular Sciences* **21**, (2020).

805   28.   Cerdeira, L. *et al.* Genomic insights of Klebsiella pneumoniae isolated from a native

806   Amazonian fish reveal wide resistome against heavy metals, disinfectants, and

807   clinically relevant antibiotics. *Genomics* **112**, (2020).

808   29.   Redondo-Salvo, S. *et al.* Pathways for horizontal gene transfer in bacteria revealed by

809   a global map of their plasmids. *Nature Communications* **11**, (2020).

810   30.   Mounsey, O. *et al.* Limited phylogenetic overlap between fluoroquinolone-resistant

811   Escherichia coli isolated on dairy farms and those causing bacteriuria in humans living

812   in the same geographical region. *Journal of Antimicrobial Chemotherapy* **76**, (2021).

813   31.   Hanage, W. P. Two health or not two health? That is the question. *MBio* **10**, e00550-19

814   (2019).

815   32.   Ludden, C. *et al.* One health genomic surveillance of escherichia coli demonstrates

816   distinct lineages and mobile genetic elements in isolates from humans versus livestock.

817   *mBio* **10**, (2019).

818   33.   Mughini-Gras, L. *et al.* Attributable sources of community-acquired carriage of

819   Escherichia coli containing β-lactam antibiotic resistance genes: a population-based

820   modelling study. *The Lancet Planetary Health* **3**, (2019).

821   34.   Shen, C. *et al.* Dynamics of mcr-1 prevalence and mcr-1-positive Escherichia coli after

822   the cessation of colistin use as a feed additive for animals in China: a prospective

cross-sectional and whole genome sequencing-based molecular epidemiological study.

The Lancet Microbe **1**, e34–e43 (2020).

35.   Hilpert, C., Bricheux, G. & Debroas, D. Reconstruction of plasmids by shotgun

sequencing from environmental DNA: Which bioinformatic workflow? *Briefings in*

Bioinformatics **22**, (2021).

36.   Antipov, D., Raiko, M., Lapidus, A. & Pevzner, P. A. Plasmid detection and assembly

in genomic and metagenomic data sets. *Genome Research* **29**, (2019).

37.   Liu, Y.-Y. *et al.* Emergence of plasmid-mediated colistin resistance mechanism MCR-

1 in animals and human beings in China: a microbiological and molecular biological

study. *The Lancet infectious diseases* **16**, 161–168 (2016).

38.   Cantón, R., González-Alba, J. M. & Galán, J. C. CTX-M enzymes: Origin and

diffusion. *Frontiers in Microbiology* vol. 3 (2012).

39.   Sekizuka, T. *et al.* Complete sequencing of the bla NDM-1-positive IncA/C plasmid

from Escherichia coli ST38 isolate suggests a possible origin from plant pathogens.

PLoS ONE **6**, (2011).

40.   Lipworth, S. *et al.* Ten-year longitudinal molecular epidemiology study of Escherichia

coli and Klebsiella species bloodstream infections in Oxfordshire, UK. *Genome*

Medicine **13**, (2021).

41.   Redondo-Salvo, S. *et al.* COPLA, a taxonomic classifier of plasmids. *BMC*

Bioinformatics **22**, (2021).

42.   Rozwandowicz, M. *et al.* Plasmids carrying antimicrobial resistance genes in

Enterobacteriaceae. *Journal of Antimicrobial Chemotherapy* **73**, (2018).

43.   Matlock, W. *et al.* Genomic network analysis of environmental and livestock F-type

plasmid populations. *ISME Journal* **15**, (2021).

44.   Ondov, B. D. *et al.* Mash: Fast genome and metagenome distance estimation using

MinHash. *Genome Biology* **17**, (2016).

45.   Figueras, M. J., Beaz-Hidalgo, R., Hossain, M. J. & Liles, M. R. Taxonomic affiliation

of new genomes should be verified using average nucleotide identity and multilocus

phylogenetic analysis. *Genome Announcements* **2**, (2014).

46.   Rosenberg, A. & Hirschberg, J. V-Measure: A conditional entropy-based external

cluster evaluation measure. in *EMNLP-CoNLL 2007 - Proceedings of the 2007 Joint*

Conference on Empirical Methods in Natural Language Processing and

Computational Natural Language Learning (2007).

47.   Orlek, A. *et al.* Ordering the mob: Insights into replicon and MOB typing schemes

from analysis of a curated dataset of publicly available plasmids. *Plasmid* **91**, (2017).

48.   Kizny Gordon, A. *et al.* Genomic dynamics of species and mobile genetic elements in

a prolonged blaIMP-4-associated carbapenemase outbreak in an Australian hospital.

Journal of Antimicrobial Chemotherapy **75**, (2020).

49.   Riley, M. A. & Gordon, D. M. A survey of Col plasmids in natural isolates of

Escherichia coli and an investigation into the stability of Col-plasmid lineages. *Journal*

of General Microbiology **138**, (1992).

50.   Lyimo, B. *et al.* IncF plasmids are commonly carried by antibiotic resistant

Escherichia coli isolated from drinking water sources in northern Tanzania.

International Journal of Microbiology **2016**, (2016).

51.   Irrgang, A. *et al.* CTX-M-15-producing E. coli isolates from food products in Germany

are mainly associated with an IncF-type plasmid and belong to two predominant clonal

E. coli lineages. *Frontiers in Microbiology* **8**, (2017).

52.   Rodríguez-Beltrán, J., DelaFuente, J., León-Sampedro, R., MacLean, R. C. & San

Millán, Á. Beyond horizontal gene transfer: the role of plasmids in bacterial evolution.

Nature Reviews Microbiology vol. 19 (2021).

53.   Navon-Venezia, S., Kondratyeva, K. & Carattoli, A. Klebsiella pneumoniae: A major

worldwide source and shuttle for antibiotic resistance. *FEMS Microbiology Reviews*

vol. 41 (2017).

54.   Pesesky, M. W., Tilley, R. & Beck, D. A. C. Mosaic plasmids are abundant and

unevenly distributed across prokaryotic taxa. *Plasmid* **102**, (2019).

55.   Fritz, S. A. & Purvis, A. Selectivity in mammalian extinction risk and threat types: A

new measure of phylogenetic signal strength in binary traits. *Conservation Biology* **24**,

(2010).

56.   David, S. *et al.* Integrated chromosomal and plasmid sequence analyses reveal diverse

modes of carbapenemase gene spread among Klebsiella pneumoniae. *Proc Natl Acad*

Sci U S A **117**, (2020).

57.   Pitout, J. D. D. & DeVinney, R. Escherichia coli ST131: A multidrug-resistant clone

primed for global domination. *F1000Research* vol. 6 (2017).

58.   Liu, C. M. *et al.* Escherichia coli ST131-H22 as a foodborne uropathogen. *mBio* **9**,

(2018).

59.   Mohsin, J. *et al.* Plasmid-Mediated Colistin Resistance Gene mcr-1 in an Escherichia

coli ST10 Bloodstream Isolate in the Sultanate of Oman. *Microbial Drug Resistance*

24, (2018).

60.   García-Meniño, I. *et al.* Swine enteric colibacillosis in Spain: Pathogenic potential of

mcr-1 ST10 and ST131 E. Coli Isolates. *Frontiers in Microbiology* **9**, (2018).

61.   Nicholas Noll, M. M. R. A. N. PanGraph: scalable bacterial pan-genome graph

construction. *bioRxiv* (2022).

62.   Richter, T. K. S. *et al.* Responses of the Human Gut Escherichia coli Population to

Pathogen and Antibiotic Disturbances . *mSystems* **3**, (2018).

63.   Forster, S. C. *et al.* A human gut bacterial genome and culture collection for improved

metagenomic analyses. *Nature Biotechnology* **37**, (2019).

64.   Sender, R., Fuchs, S. & Milo, R. Revised Estimates for the Number of Human and

Bacteria Cells in the Body. *PLoS Biology* **14**, (2016).

65.   Martinson, J. N. v. & Walk, S. T. Escherichia coli Residency in the Gut of Healthy

Human Adults . *EcoSal Plus* **9**, (2020).

66.   Martinson, J. N. V. *et al.* Rethinking gut microbiome residency and the

Enterobacteriaceae in healthy human adults. *ISME Journal* **13**, (2019).

67.   Rodrigues, C. *et al.* High Prevalence of Klebsiella pneumoniae in European Food

Products: a Multicentric Study Comparing Culture and Molecular Detection Methods.

Microbiology Spectrum **10**, (2022).

68.   Wick, R. R., Judd, L. M., Gorrie, C. L. & Holt, K. E. Unicycler: Resolving bacterial

genome assemblies from short and long sequencing reads. *PLoS Computational*

Biology **13**, (2017).

69.   Bankevich, A. *et al.* SPAdes: A new genome assembly algorithm and its applications

to single-cell sequencing. *Journal of Computational Biology* **19**, (2012).

70.   Li, H. Minimap and miniasm: Fast mapping and de novo assembly for noisy long

sequences. *Bioinformatics* **32**, (2016).

71.   Vaser, R., Sović, I., Nagarajan, N. & Šikić, M. Fast and accurate de novo genome

assembly from long uncorrected reads. *Genome Research* **27**, (2017).

72.   Walker, B. J. *et al.* Pilon: An integrated tool for comprehensive microbial variant

detection and genome assembly improvement. *PLoS ONE* **9**, (2014).

73.   Torsten Seeman. mlst. (2017).

74.   Jolley, K. A. & Maiden, M. C. J. BIGSdb: Scalable analysis of bacterial genome

variation at the population level. *BMC Bioinformatics* **11**, (2010).

75.   Jolley, K. A., Bray, J. E. & Maiden, M. C. J. Open-access bacterial population

genomics: BIGSdb software, the PubMLST.org website and their applications [version

1; referees: 2 approved]. *Wellcome Open Research* **3**, (2018).

76.   Katz, L. *et al.* Mashtree: a rapid comparison of whole genome sequence files. *Journal*

of Open Source Software **4**, (2019).

77.   Pruitt, K. D., Tatusova, T. & Maglott, D. R. NCBI reference sequences (RefSeq): A

curated non-redundant sequence database of genomes, transcripts and proteins. *Nucleic*

Acids Research **35**, (2007).

78.   Seemann, T. Prokka: Rapid prokaryotic genome annotation. *Bioinformatics* **30**, (2014).

79.   Torsten Seeman. Abricate. (2015).

80.   Carattoli, A. *et al.* In Silico detection and typing of plasmids using plasmidfinder and

plasmid multilocus sequence typing. *Antimicrobial Agents and Chemotherapy* **58**,

(2014).

81.   Siguier, P., Perochon, J., Lestrade, L., Mahillon, J. & Chandler, M. ISfinder: the

reference centre for bacterial insertion sequences. *Nucleic Acids Res* **34**, (2006).

82.   Pal, C., Bengtsson-Palme, J., Rensing, C., Kristiansson, E. & Larsson, D. G. J.

BacMet: Antibacterial biocide and metal resistance genes database. *Nucleic Acids*

Research **42**, (2014).

83.   Feldgarden, M. *et al.* AMRFinderPlus and the Reference Gene Catalog facilitate

examination of the genomic links among antimicrobial resistance, stress response, and

virulence. *Scientific Reports* **11**, (2021).

84.   Robertson, J. & Nash, J. H. E. MOB-suite: software tools for clustering, reconstruction

and typing of plasmids from draft assemblies. *Microb Genom* **4**, (2018).

85.   Csardi, G. & Nepusz, T. The igraph software package for complex network research.

InterJournal Complex Systems **Complex Sy**, (2006).

86.   Tettelin, H., Riley, D., Cattuto, C. & Medini, D. Comparative genomics: the bacterial

pan-genome. *Current Opinion in Microbiology* vol. 11 (2008).

87.   Yamashita, A., Sekizuka, T. & Kuroda, M. Characterization of antimicrobial resistance

dissemination across plasmid communities classified by network analysis. *Pathogens*

3, (2014).

88.   Branger, C. *et al.* Extended-spectrum β-lactamase-encoding genes are spreading on a

wide range of escherichia coli plasmids existing prior to the use of third-generation

cephalosporins. *Microbial Genomics* **4**, (2018).

89.   Acman, M., van Dorp, L., Santini, J. M. & Balloux, F. Large-scale network analysis

captures biological features of bacterial plasmids. *Nature Communications* **11**, (2020).

90.   Jesus, T. F. *et al.* Plasmid ATLAS: Plasmid visual analytics and identification in high-

Throughput sequencing data. *Nucleic Acids Research* **47**, (2019).

91.   Matlock, W. *et al.* Flanker: a tool for comparative genomics of gene flanking regions.

Microb Genom **7**, (2021).

92.   Arcilla, M. S. *et al.* Dissemination of the mcr-1 colistin resistance gene. *The Lancet*

infectious diseases **16**, 147–149 (2016).

93.   Zhi, S. *et al.* Assessing host-specificity of Escherichia coli using a supervised learning

logic-regression-based analysis of single nucleotide polymorphisms in intergenic

regions. *Molecular Phylogenetics and Evolution* **92**, (2015).

94.   Delihas, N. Intergenic regions of Borrelia plasmids contain phylogenetically conserved

RNA secondary structure motifs. *BMC Genomics* **10**, (2009).

95.   Blondel, V. D., Guillaume, J. L., Lambiotte, R. & Lefebvre, E. Fast unfolding of

969   communities in large networks. *Journal of Statistical Mechanics: Theory and*

970   *Experiment* **2008**, (2008).

971   96.   Tonkin-Hill, G. *et al.* Producing polished prokaryotic pangenomes with the Panaroo

972   pipeline. *Genome Biology* **21**, (2020).

973   97.   Katoh, K. & Standley, D. M. MAFFT multiple sequence alignment software version 7:

974   Improvements in performance and usability. *Molecular Biology and Evolution* **30**,

975   (2013).

976   98.   Minh, B. Q. *et al.* IQ-TREE 2: New Models and Efficient Methods for Phylogenetic

977   Inference in the Genomic Era. *Molecular Biology and Evolution* **37**, (2020).

978   99.   Minh, B. Q., Nguyen, M. A. T. & von Haeseler, A. Ultrafast approximation for

979   phylogenetic bootstrap. *Molecular Biology and Evolution* **30**, (2013).

980   100.   Yu, G., Smith, D. K., Zhu, H., Guan, Y. & Lam, T. T. Y. ggtree: an r package for

981   visualization and annotation of phylogenetic trees with their covariates and other

982   associated data. *Methods in Ecology and Evolution* **8**, (2017).

983   101.   Orme, D. The caper package : comparative analysis of phylogenetics and evolution in

984   R. *R package version 0.5, 2* (2013).

985   102.   Waters, N. R., Abram, F., Brennan, F., Holmes, A. & Pritchard, L. Easy phylotyping

986   of Escherichia coli via the EzClermont web app and command-line tool. *Access*

987   *Microbiology* **2**, (2020).

988   103.   Schliep, K. P. phangorn: Phylogenetic analysis in R. *Bioinformatics* **27**, (2011).

989   104.   Drake, J. W. A constant rate of spontaneous mutation in DNA-based microbes. *Proc*

990   *Natl Acad Sci U S A* **88**, (1991).

105. Foster, P. L., Lee, H., Popodi, E., Townes, J. P. & Tang, H. Determinants of

spontaneous mutation in the bacterium Escherichia coli as revealed by whole-genome

sequencing. *Proc Natl Acad Sci U S A* **112**, (2015).

106. Wielgoss, S. *et al.* Mutation rate dynamics in a bacterial population reflect tension

between adaptation and genetic load. *Proc Natl Acad Sci U S A* **110**, (2013).

107. Ghalayini, M. *et al.* Evolution of a dominant natural isolate of Escherichia coli in the

human gut over the course of a year suggests a neutral evolution with reduced effective

population size. *Applied and Environmental Microbiology* **84**, (2018).

108. Holt, K. E. *et al.* Tracking the establishment of local endemic populations of an

emergent enteric pathogen. *Proc Natl Acad Sci U S A* **110**, (2013).

109. Wick, R. R., Schultz, M. B., Zobel, J. & Holt, K. E. Bandage: Interactive visualization

of de novo genome assemblies. *Bioinformatics* **31**, (2015).

110. Gómez-Rubio, V. ggplot2 - Elegant Graphics for Data Analysis (2nd Edition) .

Journal of Statistical Software **77**, (2017).

111. Munday, E. BioRender. *N/a* (2021).

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 Fig. 2 Cross-compartmental, near-identical plasmids.

 (a) Count of plasmids in near-identical plasmid groups, coloured by compartment (total

 n=712 plasmids). Median size of plasmid within groups increases from left to right. **(b)**

 Proportion of plasmid host species by group. **(c)** Predicted mobility of plasmid. **(d)** AMR

 gene carriage in plasmid.

 Fig. 3. Genetically similar plasmids share between compartments

 (a) Size of plasmid clusters with at least 10 members, coloured by compartment. Size of

 clusters decreases from left to right. **(b)** Proportion of plasmid host species by cluster. **(c)**

 Plasmid mobility class and size: Left hand axis shows proportion of plasmids with a predicted

 mobility class by cluster. Right hand axis shows plasmid length boxplots by cluster. **(d)**

 Proportions of AMR gene carriage by cluster. **(e)** Plasmid core and accessory genomes: Left

 hand axis shows the count of core and accessory coding sequences (CDS) by cluster. Right

 hand axis shows plasmid core gene proportion (i.e., plasmid core CDS/total plasmid CDS)

 boxplots by cluster.

 Fig. 4. Cluster 2 plasmid and host evolution

 (a) Consensus gene ordering for plasmid cluster 2, coloured by gene type (total *n*=99

 plasmids; *n*=1 *S. enterica* isolate omitted). Genes are coloured by core, accessory, or

 transposase. **(b)** Plasmid core gene phylogeny with tips coloured by sampling compartment.

 The grey circle highlights the clade of *n*=44 plasmids which were further analysed. **(c)**

 Plasmid host chromosome core gene phylogeny with tips coloured by sampling compartment.

 Plasmid and host phylogeny tips are connected in a 'tanglegram' which connects pairs of

 plasmids and chromosomes from the same isolate. **(d)** Visualisation of the pangraph for *n*=44

 plasmids in the grey-circled clade in (b). Blocks are coloured by presence in plasmids. **(e)**

 Core blocks (found in at least 95% of the *n*=44 plasmids). **(f)** Accessory blocks (found in less

 than 95% of the *n*=44 plasmids).

a Plasmid consensus gene synteny

b Plasmid core gene phylogeny

c Chromosome core gene phylogeny

No. nucleotide substitutions per site

Gene type
- Absent
- Core
- Accessory
- Transposase

Compartment
- BSI
- Environmental
- Livestock
- WwTW

Phylogroup
- A
- B1
- B2
- C
- D
- G

Pangraph

Block type
- Core
- Accessory

d

Core blocks

e

Accessory blocks

f