

Parameters for one health genomic surveillance of *Escherichia coli* from Australia

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Genomics is a cornerstone of modern pathogen epidemiology yet demonstrating transmission in a One Health context is challenging, as strains circulate and evolve within and between diverse hosts and environments. To identify phylogenetic linkages and better define relevant measures of genomic relatedness in a One Health context, we collated 5471 *Escherichia coli* genome sequences from Australia originating from humans ($n = 2996$), wild animals ($n = 870$), livestock ($n = 649$), companion animals ($n = 375$), environmental sources ($n = 292$) and food ($n = 289$) spanning over 36 years. Of the 827 multi-locus sequence types (STs) identified, 10 STs were commonly associated with cross-source genomic clusters, including the highly clonal ST131, pandemic zoonotic lineages such as ST95, and emerging human ExPEC ST1193. Here, we show that assessing genomic relationships at ≤ 100 SNP threshold enabled detection of cross-source linkage otherwise obscured when applying typical outbreak-oriented relatedness thresholds (≤ 20 SNPs) and should be considered in interrogation of One Health genomic datasets.

Understanding the complexity of microbial transmission networks from a One Health perspective has become a priority because of their relevance for the study and management of infectious disease and antimicrobial resistance (AMR)¹. The formation of the One Health High-Level Expert Panel (OHHLEP) in 2021², comprising the Food and Agriculture Organisation (FAO), the World Organisation for Animal Health (WOAH), the United Nations Environment Programme (UNEP),

and the World Health Organisation (WHO), signals the need for urgent adoption of One Health principles by public health and research initiatives.

Escherichia coli, a well-studied member of the Enterobacterales family, is commonly host-associated while also capable of thriving in diverse environments including water and soil. It is both a common commensal and pathogen, responsible for intestinal and

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extraintestinal infections in humans and animals^{3–7}, respectively referred to as intestinal pathogenic *E. coli* (IPEC) and extraintestinal pathogenic *E. coli* (ExPEC), and a contaminant of agricultural crops and food products^{8,9}. Reservoirs of such pathogens have been identified across livestock, wildlife, and the environment^{10–12}. Furthermore, while the role of environmental *E. coli* populations in AMR dissemination requires further exploration, waste processing systems expose *E. coli* to pressures that can trigger the uptake of resistance mechanisms¹³. The extensive diversity of *E. coli*, some of which are zoonotic, and their widespread capacity to share mobile genetic elements that carry AMR and virulence gene cargo underline the importance of surveillance of this One Health pathogen.

Over the last decade genomic surveillance has become a common tool for investigating human pathogens and outbreaks^{1,14–16}, while the WHO's Tricycle project is a key example of a multisectoral surveillance initiative focussed on Extended-Spectrum Beta-Lactamase (ESBL) carrying *Escherichia coli*¹⁷. In this regard, development of genomics-enabled prospective surveillance systems will be an important step in monitoring the emergence of AMR across sectors. So too will be the establishment of sophisticated workflows for sampling, genomic sequencing and bioinformatic analyses to generate fit-for-purpose microbial genomic surveillance datasets. Currently there is little consensus regarding the approaches required to demonstrate linkages, direct or otherwise, between members of microbial communities co-occurring between distinct hosts and environments. Modern outbreak-related investigations for enteric pathogens increasingly utilises core-genome multi-locus sequence typing (cgMLST) in combination with single nucleotide polymorphism (SNP)-based approaches^{18–22}, the former being used to rapidly cluster genomes into potentially epidemiologically relevant subsets and the latter generally used for high resolution phylogenetic analysis. However, the utility of such approaches in analysing large-scale, diverse (including spatial, temporal, and host/environment diversity) genomic datasets for evidence of potential cross-source linkage is poorly understood.

Here, utilising a large national multi-sectoral genomic dataset, we explore cgMLST and SNP-based approaches in the identification of cross-source clusters and potential transmission events in *E. coli* and highlight their relevance within a One Health context. Our findings serve as a model for analysis of datasets for *E. coli*, and potentially other Genera, and inform the planning and operation of prospective bacterial genomic surveillance infrastructure nationally and abroad.

Results

Collection characteristics

In total, 5471 Australian *E. coli* genomes originating from humans ($n = 2996/5471$, 54.76%), wild animals ($n = 870/5471$, 15.90%), livestock ($n = 649/5471$, 11.86%), companion animals ($n = 375/5471$, 6.85%), environmental sources ($n = 292/5471$, 5.33%) and food (289/5471, 5.28%) were analysed. Collection dates ranged from 1986 to 2022, with 98.32% ($n = 5379/5471$) collected between 2001 and 2022. While most samples originated from Victoria and New South Wales, the dataset contains samples from all states and territories (Fig. 1A). Where such data was available, 76.70% (2298/2996) of human samples were identified as from clinical sources. In total, 52.60% ($n = 1576/2996$) of human samples were sourced from extraintestinal sites, while 32.57% ($n = 976/2996$) originate from intestinal sites, and 14.75% ($n = 442/2996$) lacked the appropriate metadata. Among livestock sourced samples, 47.92% ($n = 311/649$) originate from extraintestinal sites, while 35.43% ($n = 230/649$) originate from intestinal sites and 16.64% ($n = 108/649$) unable to be assigned to either category (Fig. 1B).

Phylogenetics

We identified 8 *sensu stricto* phylogroups within the collection, the most frequently identified being B2 which comprised 39.76% ($n = 2175/5471$) of genomes. Phylogroups A, D and B1 were present at

comparable frequencies; 17.46% [$n = 955/5471$], 14.48% [$n = 792/5471$] and 12.81% [$n = 701/5471$], respectively. Most B2 ($n = 1637/2164$; 75.26%) and D ($n = 481/803$; 60.73%) genomes were from humans. While 36.23% ($n = 346/968$) of phylogroup A and 25.39% ($n = 178/701$) of phylogroup B1 genomes were from humans, the majority were sourced from wild animals (A: $n = 213/968$; B1: $n = 213/701$), livestock (A: $n = 231/968$; B1: $n = 84/711$) and environmental (A: $n = 68/968$; B1: $n = 120/711$) sources (Fig. 2).

Phylogroups F, E, G and C were less common (Fig. 2). In total, 827 STs were identified. The collection was phylogenetically diverse (Fig. 2) but predominantly comprised of a small number of STs; while we identified 475 singleton STs, the top thirty STs comprised 61.63% ($n = 3372/5471$) of the collection.

Identification of STs implicated in cross-source clusters

Within outbreak settings, direct or indirect transmission can be inferred by the concurrence of closely related genomes across different sources in combination with epidemiologically informative metadata. While our dataset lacks the latter, the former may provide sufficient evidence to indicate complex and likely protracted movement of strains in either direction (or potentially both) that can be further investigated. We thus sought insight into potential cross-source genomic clusters observed among the sequence types under analysis. cgMLST was used to determine pairwise allelic distances between genomes and genomic clusters were defined as two or more genomes which exhibit an allelic distance of ≤ 40 . In total, 3465 isolates (comprising 151,994 isolate pairs) were identified as putative clusters; the remaining 2006 isolates exceeded this distance from any other isolate in the collection (Fig. 2). Note that clusters in this context does not indicate outbreak associated clusters.

Isolates within ten sequence types (STs 131, 963, 1193, 95, 69, 80, 117, 457, 648 and 57) comprised 35.60% ($n = 1,948/5471$) of the overall collection (Fig. 2C). Putative cross-source clusters within these sequence types were investigated further, using pairwise SKA Single Nucleotide Polymorphism (SNP) analyses (Fig. 3). A preliminary analysis was used to assess the SNP distance among these STs at which cross-source clusters were identified (Supplementary Fig. 1). Clusters were defined as two or more isolates differing by ≤ 100 SNPs. This cut-off is more conservative than that used to identify putative clusters (≤ 40 allelic distance [cgMLST]) but allows for a greater degree of phylogenetic distance than typical clinically defined SNP distance thresholds. The tested cluster metrics lacked consensus with inconsistent support for the ≤ 100 SNPs cut-off threshold (Supplementary Fig. 5). However, additional supplementary analysis using an additional population clustering framework, PopPunk²³, supported our clustering approach, with all clusters identified using our cgMLST threshold falling within the same PopPunk clusters (Supplementary Information). Of the 92,702 cross-source pairs (pairwise combinations of 1948 strains) analysed, just 2,443/92,702 of pairs (2.65%), comprising 541 strains, exhibited SNP distances ≤ 100 SNPs. The SNP distance thresholds were further classified as follows: > 75 and ≤ 100 ($n = 1014/92,702$; 1.10%; strain count = 474), > 50 and ≤ 75 ($n = 1005/92,702$; 1.09%, 329 strains), or > 20 and ≤ 50 ($n = 421/89,491$; 0.46%; 136 strains). Just three isolate pairs, comprising 5 strains, exhibited SNP distances ≤ 20 SNPs, comprising less than 0.1% of the phylogenetic relationships. Utilising a SNP threshold of ≤ 100 rather than ≤ 20 therefore resulted in an 814-fold increase in identification of cross-source pairs, while still requiring isolates to exhibit a high degree of phylogenetic similarity.

Within the top 10 STs 158 clusters emerged, each comprising two or more isolates differing by ≤ 100 SNPs. Of these, 31 comprised cross-source clusters which had minimum cluster size of 2, a median of 10 and a maximum of 251 (Table 1). Cluster counts varied greatly by ST (Table 1); a network analysis of these clusters, stratified by ST, was then generated to explore the potential interconnectivity of sources (Fig. 4).

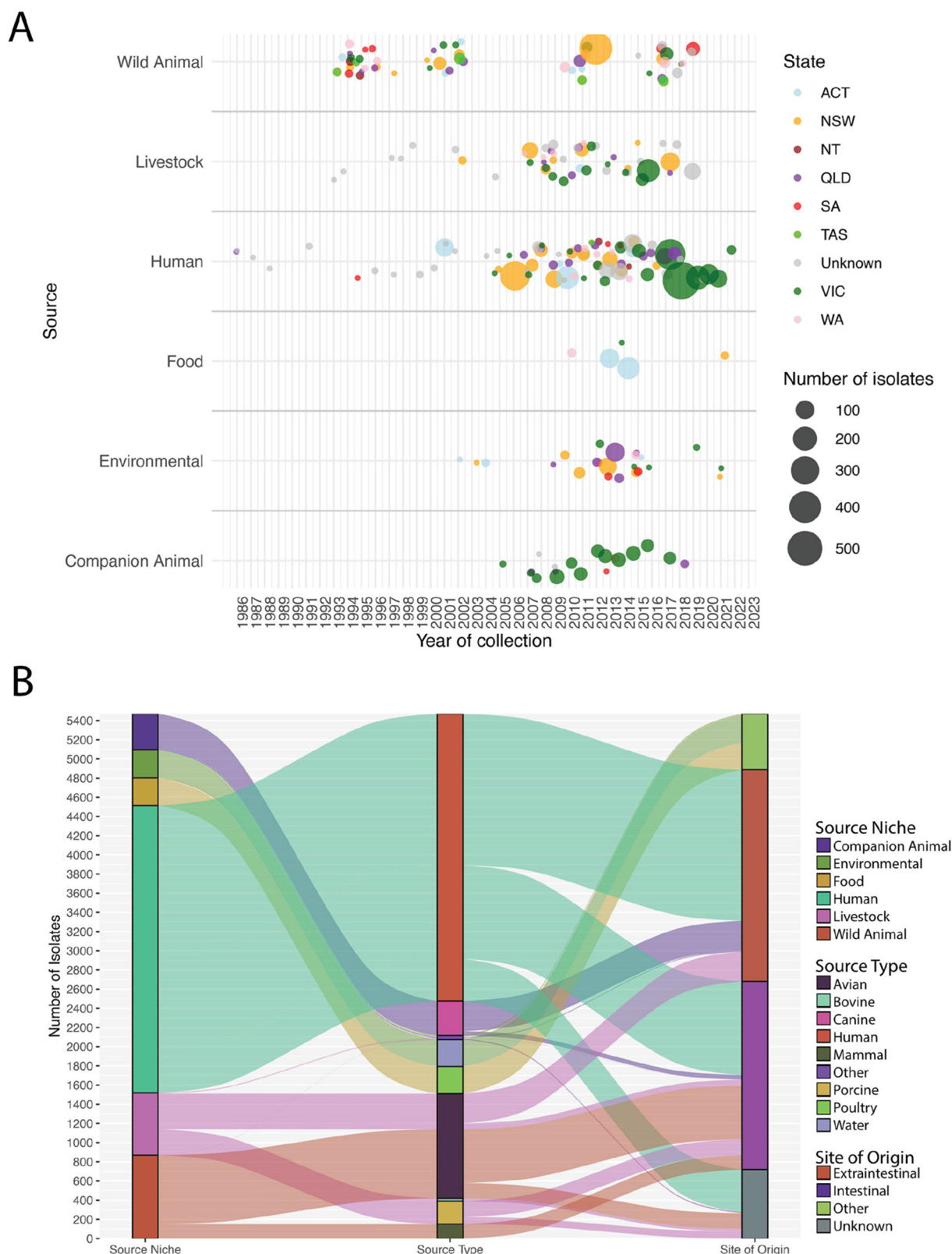


Fig. 1 | Composition of the collection. A Timeline of samples in the dataset by source and state or territory of origin. **B** Alluvial diagram visualising the broad source of genomes (left column), species, or type grouping of samples (centre column) and

extraintestinal or intestinal sample isolation (right column). Labels for species or type have been omitted for groups with less than 10 samples, these include bovine, food, environmental, soil, marsupial, feline, reptile, caprine and 'liquid'.

Our analysis revealed ST131 was implicated in 10 cross-source clusters spanning humans, companion animals, food, livestock, and wildlife (Table 1). These exhibited a minimum, median and maximum cluster size of 2, 4 and 251, respectively. Additionally, 47 mono-source

ST131 clusters were identified among companion animals, food, wildlife and especially humans. Similar trends were also observed with ST1193, which was found to be associated with a total of 9 clusters, of which 7 spanned multiple sources and 2 originated from a single

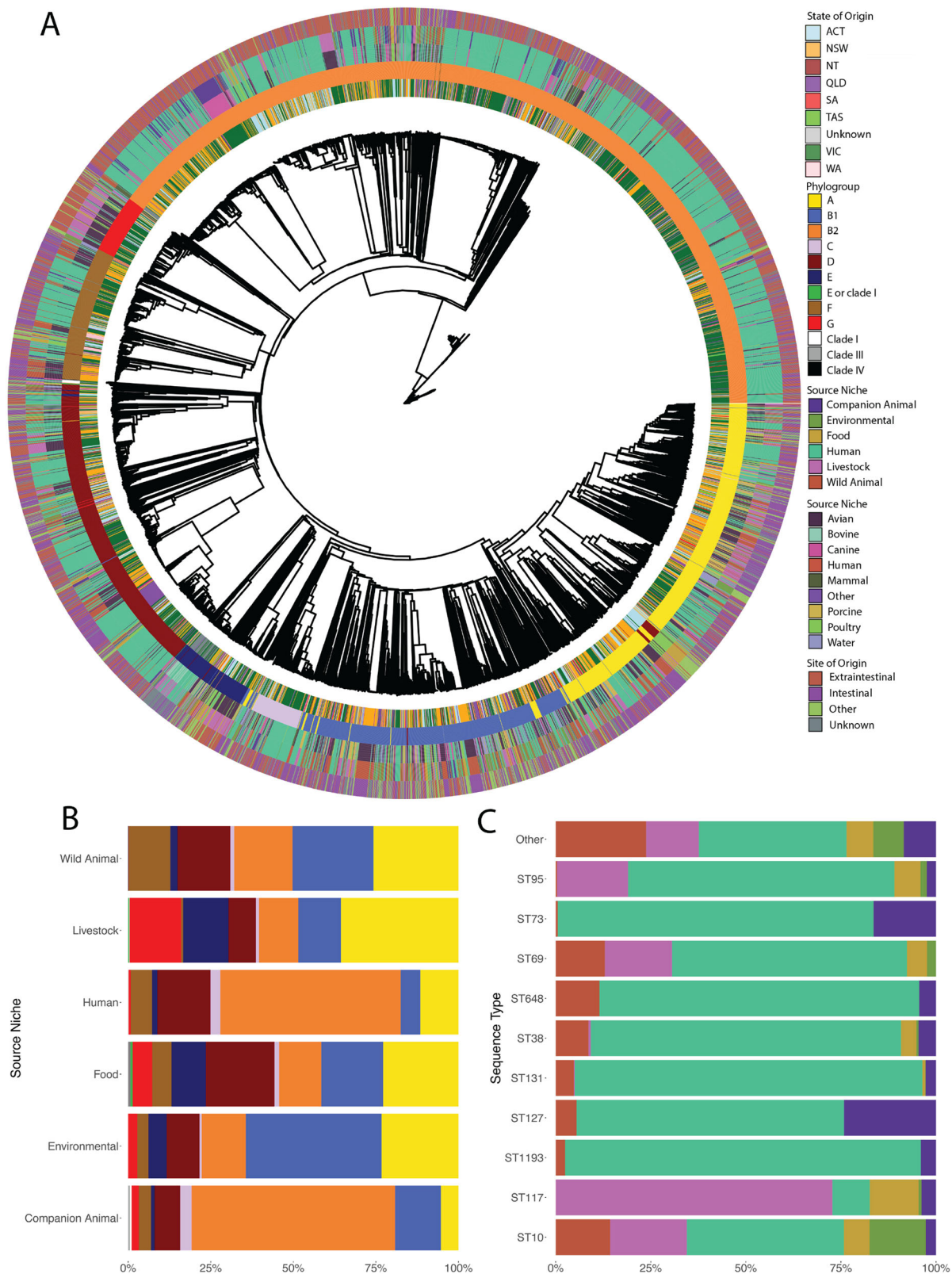


Fig. 2 | Genomic overview of the collection. A Phylogenetic tree (cgMLST-derived; see “methods”) visualizing the relatedness of the isolates under investigation. Coloured bars indicate (from innermost to outermost) i) the Australian State from which a genome originates; ii) Phylogroup association; iii) Source Niche; iv) Source Type and v) Sample type (whether Extraintestinal, Intestinal, Other or Unknown). Tree is midpoint rooted. Metadata is shown on this tree only to

demonstrate its broad associations with phylogenetic structure; data on individual genomes is available in Supplementary Data 1. **B** Intersection of phylogroup and isolate source. **C** Source Niche of the top ten sequence types. See legend to the right of panel A for phylogroup and Source Niche colours associated with panels (B and C). Note that for panel B, cryptic *E. coli* phylogroups are omitted.

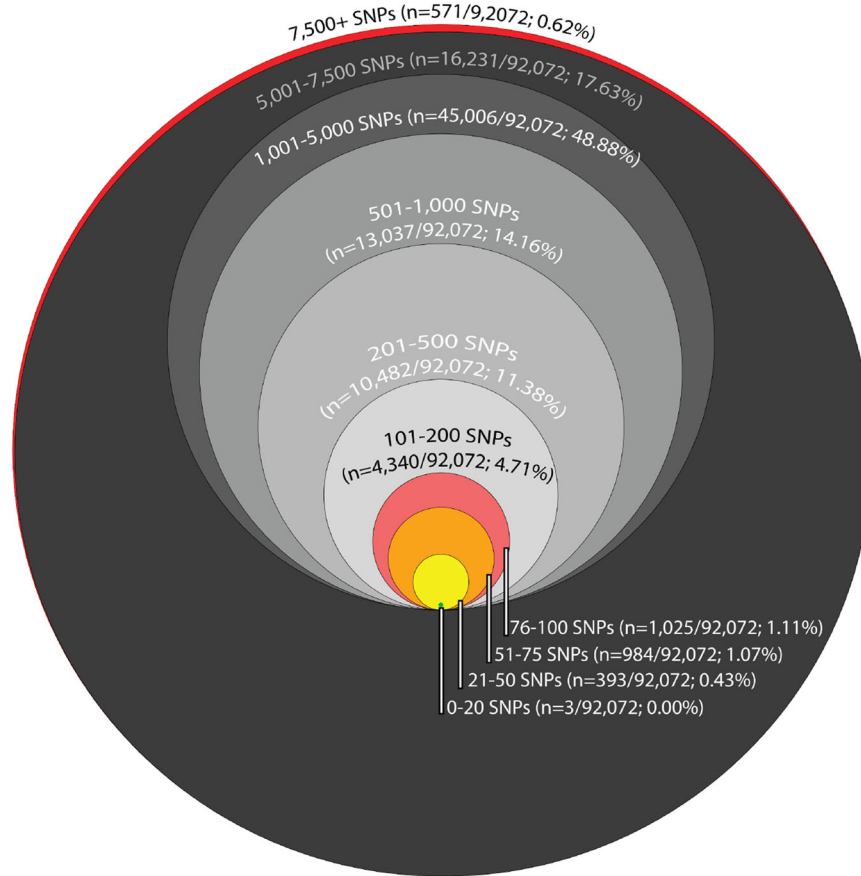


Fig. 3 | Euler diagram visualising the frequency of SNP distances amongst multi-source isolate pairs. Area for a given circle is proportional to the number of pairs at a given threshold. The highest distance detected among the ten STs under analysis was 11,350; note that SNP distances were computed only for strain pairs

sharing an ST. - Actual value = 0.03%. Note that large SNP distances (e.g., those exceeding 1000 SNPs) are less accurate than smaller SNP distances and should only be used as a guide.

source. Among ST1193's cross-source clusters, minimum, median and maximum cluster sizes were 20, 68 and 115, respectively. ST963 and ST457 were identified in a total of 3 cross-source clusters (ST963: 1; ST457: 2) spanning wild animals and humans (minimum, median and maximum cluster sizes of: ST963 - 75, 75 and 75; ST457 - 4, 10 and 16, respectively). ST963 was also found to form 2 mono-source clusters, while ST457 was found to form 11. Companion animal associated mono-source clusters were also a feature of networks involving ST131, ST1193 and ST80. Notably, while ST648 exhibited cross-source linkage at ≤ 40 allelic distance, high resolution SNP analyses identified no cross-source genomic clusters at ≤ 100 SNPs.

Four STs, ST117, ST57, ST69, and ST95 featured in poultry-associated networks, some of which were relatively large (Table 1). Regarding ST57, one cross-source cluster spanned food, livestock, and humans, while another spanned food and livestock. ST117 featured predominantly in poultry-associated mono-source clusters, though networks spanning humans, companion animals, food, and livestock were evident. Within ST69, mono-source clusters from poultry and humans predominated, however, cross-source clusters spanning wild animals and humans, and humans and food, were also identified.

We gave particular attention to the cluster network of ST95, i) due to its role as both a human and avian pathogen²⁴, and ii) as it featured a large cross-source cluster associated with a total of 30 strains, of which 51.6% ($n = 16/31$) originated from food (poultry meat), 12.9% ($n = 4/31$) from livestock (diseased poultry animals) and 35.5% ($n = 11/31$) from humans (Fig. 4A; Supplementary Data 1). Within this cluster (C1, Fig. 4A), the median SNP distance within isolate pairs was 102 (min = 15;

max = 598), while isolate pairs which were collected from different sources exhibited a SNP distance ranging from 33 to 598 (median = 104). In addition, three other clusters were identified spanning multiple sources. The first (C2, Fig. 4A) included 10 isolates, including 2 from food ($n = 2/10$; 20%) and poultry animals ($n = 8/10$; 80%), within which SNP distances between isolates collected from multiple sources ranged from 32–53 (median 81). Additionally, Cluster C3 featured 3 isolates from companion animals (canine UTIs) and 7 from humans (including isolates from UTIs and from intestinal biopsies), among which multi-source pairs exhibited SNP distances ranging from 58–94 (median = 83). We also identified large mono-source clusters, including C4, which featured 30 poultry isolates collected from diseased poultry animals between 2014 and 2016 with SNP distances ranging from 0–100 (median = 45), as well as C5, which featured 17 human-sourced isolates collected between 2006 and 2015 with SNP counts ranging from 9–100 (median = 41.5).

Exploring phylogenetic distance thresholds using cgMLST and SNP-based approaches

We explored the intersection of cgMLST and SNP-based distance metrics for the 10 STs most commonly associated with cross-source clusters (STs 131, 1193, 95, 57, 69, 117, 963, 457, 80 and 648). Due to the inherent biases within the dataset, we were unable to robustly quantify the correlation of these metrics. Nonetheless, in many instances the metrics correlate and are relatively linear in nature (Supplementary Fig. 3). Notwithstanding sampling bias, some STs appear to have a greater or lesser degree of correlation between these metrics (Supplementary Fig. 3).

Table 1 | Summary of genomic clusters in SNP-based network analysis

ST	Count of ST	Count of Clustered Genomes	Count of Clusters	Mono Sectoral Clusters	Cross Sectoral Clusters	Minimum Cross-Source Cluster Size	Median Cross-Source Cluster Size	Maximum Cross-Source Cluster Size
131	841	610	57	47	10	2	4.0	251
95	247	150	23	18	5	2	10.0	31
1193	201	153	9	7	2	20	68	115
69	170	73	19	16	3	3	3.0	6
117	132	89	17	13	4	2	2.5	16
648	113	17	8	8	0	NA	NA	NA
963	87	80	2	1	1	75	75.0	75
457	69	46	11	9	2	4	10.0	16
57	59	43	8	6	2	10	12.5	15
80	29	19	4	2	2	2	6.5	11

An allelic distance threshold of ≤ 40 identified many more strain pairing events than did a SNP distance threshold of ≤ 100 SNPs in isolation (Supplementary Fig. 4). Isolates infrequently exhibited > 40 allelic distance when SNPs were ≤ 100 , suggesting a degree of concordance between these methods. However, when visualising the relationship between allelic distance and SNP distance, we found that isolate pairs differing by ≤ 40 alleles differed by as many as 1430 SNPs (Fig. 5). Similarly, SNP counts ≤ 100 were found in isolate pairs which exhibited as many as 51 allelic distances (in which instance the isolate pair exhibited 88 SNPs).

Critically, associations between STs and particular combinations of hosts and environments based on SNP distances were also observed when employing cgMLST allelic distance-based approaches (Fig. 5). For example, STs exhibiting fewer than 100 SNPs exhibited allelic distances between 2 and 20, though isolate pairs which exhibited a greater degree of incongruence between SNP distance and allelic distance were observed; for example, ST131 isolate pairs spanning humans and wild animals exhibited low SNPs and more inflated allelic distances, whilst ST963 isolates from these same sources in some cases exhibited 604 SNPs but an allelic distance of just 4.

Phylogenetic analysis

We sought to apply phylogenetics methodology to explore cross-source linkage. As temporal data spanned 15 years, sequence types 131, 1193, and 95 were further investigated for suitability for phylogenetic analysis, however, poor temporal signal suggested this approach was not appropriate for this dataset. Root-to-tip regression was used to detect strict clock-like structure in these sequence types which revealed that all three had an R^2 below 0.1 suggesting insufficient clock-like behaviour with a strict clock model (ST95 $R^2 = 0.09$, ST1193 $R^2 = 0.02$, ST131 $R^2 = 0.0003$). STs 131 and 95 showed positive correlations and were further investigated for temporal signal using BETS. However, the analysis failed to converge to a stationary distribution, indicating a lack of suitability for phylogenetic analyses.

Discussion

Core-genome- and Kmer-based approaches are complementary in large scale One Health genomic surveillance

E. coli is the leading cause of death associated with antibiotic resistance²⁵ and a quintessential One Health pathogen, marking it as an excellent choice for interrogating complex bacterial transmission pathways using whole genome sequencing and AMR²⁶. This argument is strengthened by recent studies demonstrating the existence of naturalised environmental *E. coli* populations²⁷, and evidence that most antimicrobial resistance genes have an environmental origin²⁸. Despite this, genomic relationships between *E. coli* across humans,

animals, food, and the environment remain relatively poorly defined, as do the transmission networks underlying these relationships.

Several studies that have sought to understand bacterial transmission networks within a One Health context typically have employed relatedness thresholds that are less conservative than those used in traditional genomic epidemiological investigations of outbreak scenarios^{29,30}. There is little consensus on what levels of relatedness are appropriate, partially because of a lack of empirical evidence. Generating such evidence is problematic because of substantial knowledge gaps regarding phylogenetic diversity, and variance in rates of mutation and lateral gene transfer within and between *E. coli* sequence types. Additionally, the impact of changing environmental conditions as *E. coli* moves between hosts and environments remains poorly understood, as it relates to these evolutionary processes. These likely have significant impacts not just on the interpretation of phylogenetic analyses, but for that of phylodynamic investigations which are particularly sensitive to noise introduced by various factors, including but not limited to data associated with large online datasets.

Here we provide novel insight into the intersection of cgMLST-based and SNP-based (SKA) phylogenetic distance measurements within a One Health context to guide future research. While both methodologies are generally in agreement, some isolate pairs appear less closely related based on cgMLST analysis compared with SNP-based analyses suggest and vice versa. This disparity is likely due to the presence of distinct mobile genetic elements between isolate pairs; note that phylogenomic distance using SKA-based methods is performed on a pairwise basis, unlike that of most traditional SNP-based approaches defining a core using pangenome- or reference-based alignments.

We likely underestimate the frequency of cross-source genomic clusters using a SKA-based approach due to the inclusion of SNPs associated with accessory genome content. Future SKA-based methodologies may benefit from removal of sequence data attributed to accessory elements which are likely to inflate SKA-derived SNP values and potentially mask the otherwise close core-genome similarity of genomes under study. It is likely that F plasmids in our study may inflate these SNP values. We recently demonstrated that upwards of 78.6% of a cohort of 34,176 *E. coli* genomes carry an F plasmid representing 1161 plasmid MLSTs²⁴. F plasmids are therefore highly phylogenetically diverse and a source of potential SNPs when utilising a method which doesn't mask or omit plasmid sequences. Indeed, preliminary plasmid analyses revealed that at least 76.53% ($n = 4187/5471$) of isolates under analysis carried F-plasmid replicons (Supplementary Data 1). Future studies into F plasmids within a One Health context, and their cross-source and mono-source dissemination, may prove insightful in identifying plasmid lineages which play critical roles in the

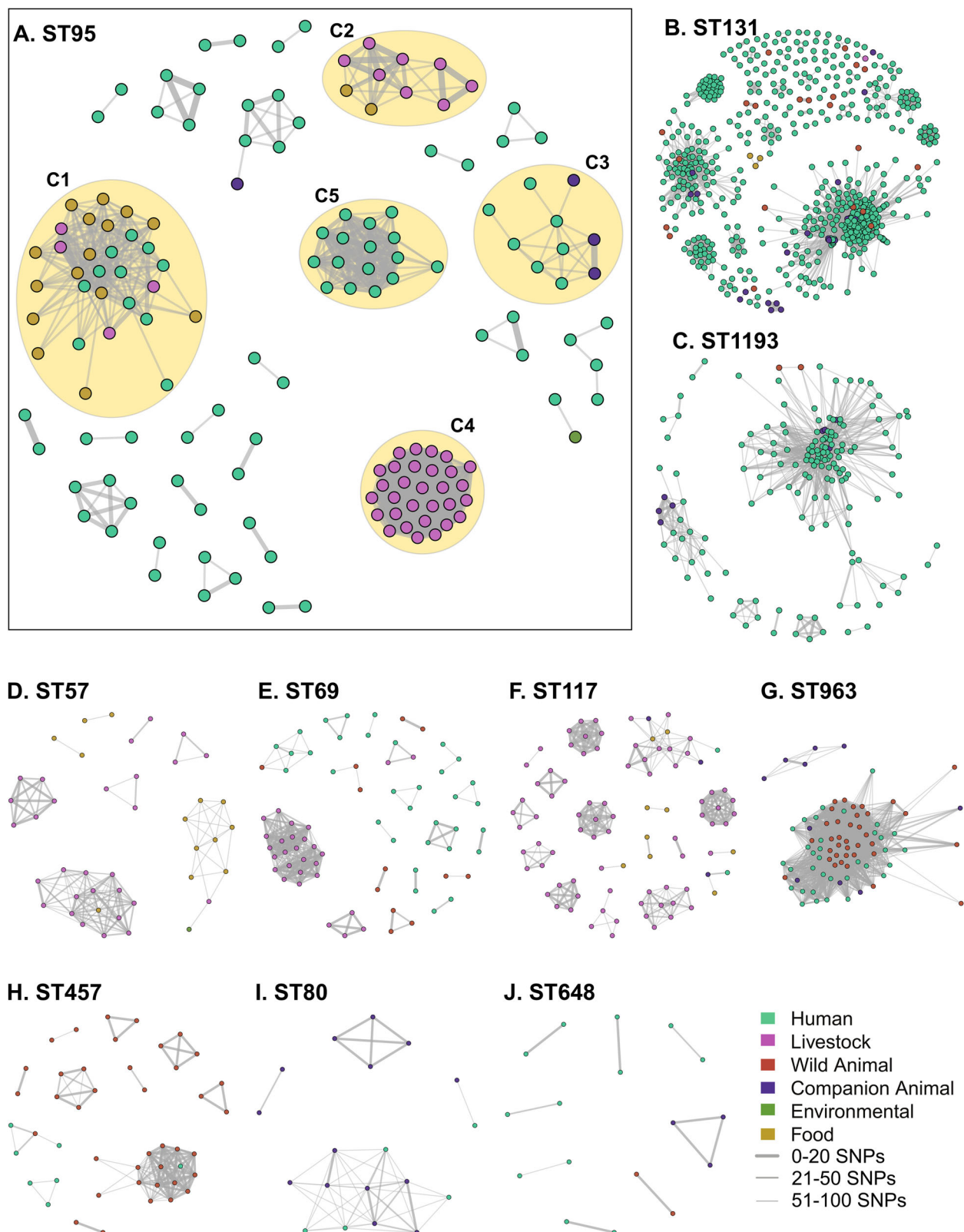


Fig. 4 | Network analyses for STs commonly associated with multi-sectoral clusters representing their intra-source and inter-source dissemination. Genomic clusters include two or more instances of genomes which have a pairwise SNP distance of ≤ 100 SNPs and are coloured by source. **A.** Highlights ST95, a common pathogen of humans and poultry. Examples of multi-source and mono-

source clusters are highlighted in yellow. **B–J** Display the networks for other STs commonly identified in the dataset with multi-sectoral clusters. SNP distances for clusters is available in Supplementary Data 2. (https://github.com/maxlcummins/APG-OHEC-Retro-MI/blob/v1.0.1/Supplementary_Material/Supplementary_Table_2.txt).

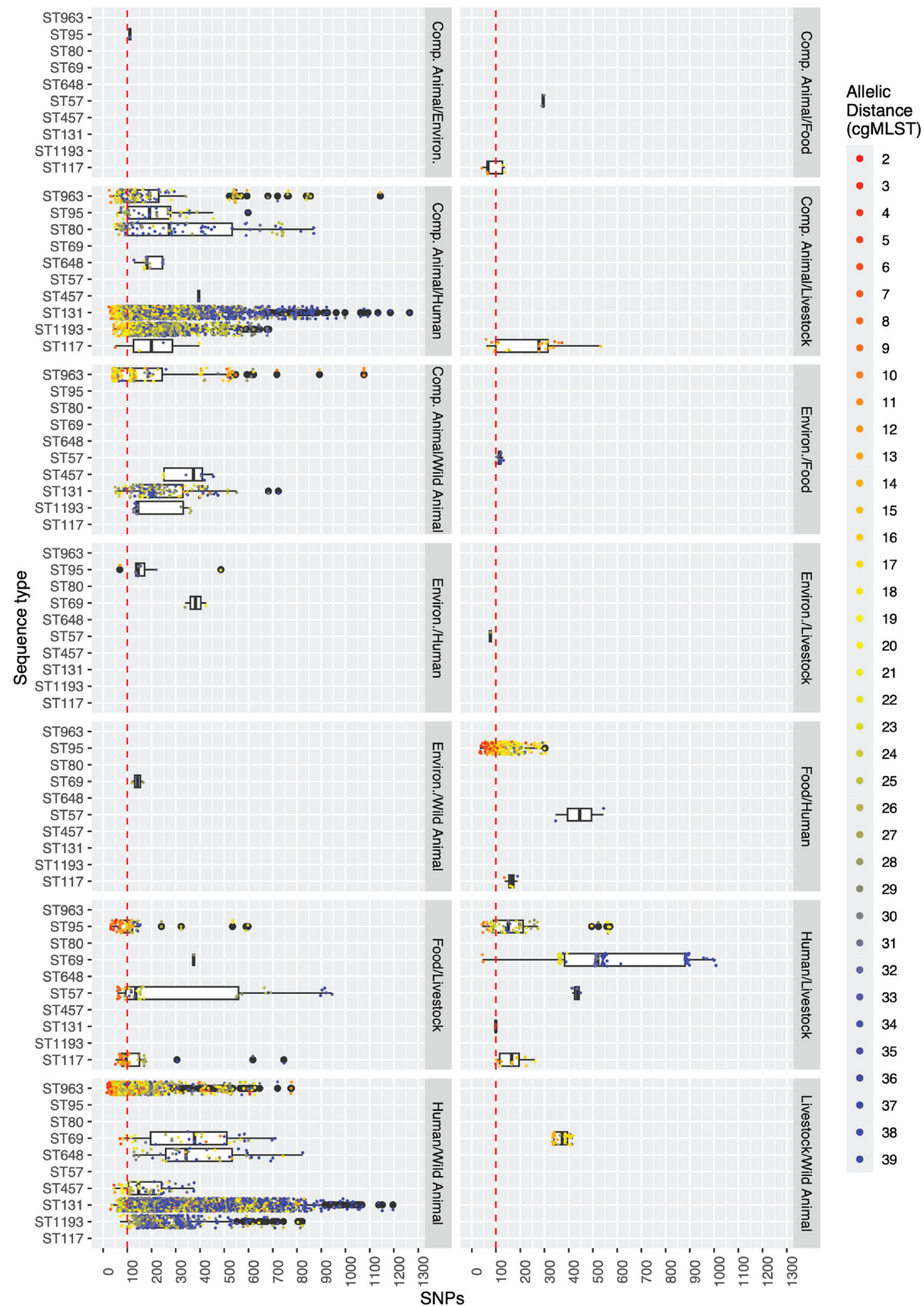


Fig. 5 | Phylogenetic distance by across sources and sequence types. This series of box plots compare the phylogenetic distances of isolate pairs (the unit under study). STs for a given pair are shown on the y-axis, SNP distances are shown on the x-axis and the colour of a data point representing a pair of isolates indicates the cgMLST distance for that pair. Counts of strain pairs for given combinations of STs and pairs of sources are available in Supplementary Data 3. Central lines within

boxplots represents the mean, while the bounds of the box indicate the first and third quartiles (25th and 75th percentiles). Whiskers extend to the minimum and maximum values. A red dotted line at 100 SNPs indicates a threshold of relatedness used to indicate moderate phylogenetic overlap. Panels visualise these parameters for pairs of isolates from the denoted pairs of sources – only isolate pairs from different sources are shown.

evolution of virulence and resistance in *E. coli* and other Enterobacterales.

A limitation of our study is that the location of SNPs among closely related genomes is indeterminate. Identifying the location of these mutations (i.e., as being intergenic or intragenic as well as chromosomal or MGE-associated) may provide insight into the mechanisms of host adaptation used by *E. coli* to allow its rapid colonisation (and infection) of a diverse range of hosts. It may also be possible to identify SNPs (or SNP combinations) with predictive power for source attribution, potentially through the use of machine learning, however this is a research area in its infancy³¹.

Additionally, due to our approach comparing SNP distances of strains which share a ST, it is likely that we underestimate the frequency of cross-source genomic clusters through omission of genome pairs which may differ by as few as one SNP which has occurred within one of the MLST-defining loci. However, without inferring directionality, our phylogenomic analyses suggest that strains that differ by 50–100 SNPs are occasionally distributed among diverse hosts or over significant geographic distances, reflecting dissemination pathways that may be complex and poorly understood. Knowledge gaps and lack of suitable analytical methodologies for SNP analyses within One Health contexts, as opposed to traditional epidemiological settings, also limit cross-study comparisons. Additional studies are therefore needed to address these gaps in the literature.

Subsequent research exploring phylogenetic distance thresholds within a One Health context should utilise datasets with rigorous sampling methodologies, particularly with genomes from isolates collected from diverse hosts and environments sampled within a fixed geographical and temporal window. We performed a supplementary analysis on a subset of genomes from a five-year window within a single Australian State seeking to identify potential genome pairs which may have been involved in more direct movements between sources due to their more proximal time and area of sampling (See Supplementary Information). While we identified genomic clusters within this period which differ by ≤ 100 SNPs both within and across sources across multiple sequence types, our sampling depth for any combination of region and sampling window was relatively low.

Snapshot studies focusing sampling efforts on a specific region and time-period would likely provide deeper insight into the relative frequency of cross-source transmission events than we are able to provide with this dataset. To demonstrate this, we also analysed a previously published cohort of 1338 *E. coli* genomes from Nairobi, Kenya (Supplementary Information) which features genomes from isolates collected from humans and their co-residing household livestock as well as rich epidemiologically useful metadata. Within this dataset, we identified clusters of genomes across a diversity of sequence types, which were collected from the same households. Our analysis (and that of the authors) suggests these clusters may be evidence of within-household transmission events.

Future studies should also contrast results from cgMLST and SKA-based approaches with additional reference-based, pangenome-based methods and other high resolution phylogenomic analyses such as wgMLST. We opted for SKA and cgMLST-based approaches due to their scalability and reference-independence. Pangenome-based analysis methods are highly computationally intensive for large sample sets, while reference-based approaches (e.g., snippy) are influenced by reference bias, and depending on the degree of intra ST diversity, require additional bioinformatic analyses to identify appropriate reference genomes²⁹. These methodological considerations are critical for scalable genomic surveillance utilising large datasets. In addition, phylogenetic methods which require distance recalculation for the entire cohort upon addition of new genomes are inherently incompatible for large scale analyses. Different STs will also exhibit a greater or lesser degree of correlation between combinations of cgMLST-based, SKA-based, and potentially other phylogenetic methods. For

example, variation in genome diversity and recombination rates within sequence types likely results in cgMLST and SNP distances being differentially impacted by acquisition of accessory gene content, complicating comparisons of these methodologies. Distance thresholds may therefore need to be fine-tuned in a sequence type-specific manner.

Global pandemic ExPEC sequence types shuttle between humans, animals, food and the environment

Utilising 5471 Australian *E. coli* genomes from humans, animals, food, and the environment spanning 36 years, we have identified *E. coli* clusters spanning every source analysed, including humans, food, companion animals, livestock, wildlife and the environment. Sequence types 131, 963, 1193, 95, 69, 80, 117, 457, 648 and 57 were most frequently associated with cross-source clusters, potentially implicating lineages residing within these sequence types in cross-source transmission. However, it is critical to note that this transmission has likely taken place across unknown periods of time via an indeterminable number of intermediate hosts and vectors. Nonetheless, this data highlights the need for a deeper understanding of: i) relevance of these STs to One Health stakeholders (for example, their zoonotic potential and/or capacity to colonise and persist on food products and man-made surfaces); ii) their carriage of resistance and virulence loci, and the mobile genetic elements that harbour these traits; iii) intra-ST diversity, and; iv) the genomic (and potentially epigenomic) underpinnings of emerging and pandemic STs.

Understanding transmission networks of zoonoses remains a key motivator for One Health genomic surveillance. It is notable that many of the genomic clusters we identified are comprised of pandemic human ExPEC STs³², including globally disseminated STs with reservoirs in companion animals^{33–35} and poultry (Avian Pathogenic *E. coli*)³⁶. While human ExPEC are overrepresented in our dataset, and thus closely related strains of major ExPEC lineages are more likely to be identified across sectors, our observations highlight the potential transmission networks which may facilitate their dissemination (Fig. 4) and earmark them for ongoing scrutiny, despite SNP distances within these genomic clusters not being indicative of these being instances of clusters of an outbreak like transmission event. While characterisation of several of these STs has been performed in Australia and abroad^{24,37–40}, substantial knowledge gaps remain. Several sequence types that were identified in our study, such as in ST69, ST117, and especially ST95, are globally disseminated pandemic avian pathogenic *E. coli* lineages that are increasingly implicated in human extra-intestinal infections^{24,32,39}. Our observations suggest that a better understanding of the potential transmission of *E. coli* from all aspects of poultry production (meat and manure) is needed. In addition, protocols are needed to ensure production and application of microbially safe poultry manures for food crop production⁴¹ and use of raw poultry as feed for companion animals. Further, our findings reinforce the need for strict biosecurity in the food production sector to minimise instances of zoonanthroponosis ('reverse zoonotic' disease transmission).

Similarly, transmission of *E. coli* isolates between humans and their companion animals (particularly dogs) has been observed in multiple STs, including ST95^{42–45}. Clonal isolates of ST131 have also been reportedly isolated from humans and canines in Europe⁴⁶. We also reported previously phylogenetic overlap between isolates of ST131 from humans, canines, wastewater and wild birds which ranged between 37 and 76 SNPs; a trend echoed further in the present dataset⁴⁷. Studies suggest municipal waste and sewage treatment sites visited by wildlife are likely to be important for the movement of ST131 and other *E. coli* STs, as well as other Enterobacterales^{38,40,47,48}. We frequently identified genomic clusters of isolates spanning humans and wild animals, particularly wild bird species. Deeper and broader sampling efforts are needed to examine the full extent by which

wildlife and waste streams may enable dissemination of AMR and emerging and pandemic pathogens.

By utilising a relatively high threshold for genomic clusters (100 SNP) we account for protracted transmission pathways potentially involving multiple vectors and reservoirs that would expose *E. coli* to diverse selection pressures^{49–51}, impacting baseline mutation rates⁵¹ and promoting genetic rearrangements of AMR associated loci⁵². Most studies on *E. coli* mutation rates have occurred in laboratory settings or single hosts⁵³ and little is known about the impact of diverse selection pressures and transmission across different matrices and lifestyles. Less conservative phylogenetic distance thresholds are therefore justified to gain an understanding of the movement of *E. coli* across sectors and the source combinations and sequence types associated with such movement. Standard clustering metrics were not useful for selecting an appropriate SNP threshold (Supplementary Fig. 5); therefore, we encourage further research on the development and validation of cluster quality indicators that are more suitable for evaluating heterogeneous One Health datasets, such as in the present study.

Here we have collected one of the largest *E. coli* datasets, however, due to the opportunistic sampling and limited metadata associated with this study, our results should be interpreted with the following considerations. Critically, while the current dataset can be used to identify genomic clusters it cannot be used to determine categorically identify transmission events, nor provide insight into the directionality of movement between different sources. Additionally, diverse sampling regimes were utilised across the more than 66 studies from which genomes were aggregated and some sequence types are over-sampled. Due to these, and other factors, STs (e.g., ST131) carrying clinically important antibiotic resistance genes predominate in our collection. While we opted not to present AMR-associations in the present work, this predisposition will bias the phylogenetic structure of the cohort being analysed. Similarly, due to the opportunistic nature of the dataset, there are limited spatiotemporal overlaps, potentially reducing the probability of detecting cross-source transmission events. Finally, within the different sectors sampled, particularly livestock and food, sample diversity is restricted, generally being derived from one or two main animal host types (swine and poultry). Despite these limitations, there are valuable signals in a dataset of this size, the use of which is critical for informing the development of future surveillance efforts. Of significance, and despite this sampling bias, we found many mono-source and cross-source clusters across a breadth of STs, shedding light on potential transmission networks.

Future genomic surveillance efforts require rigorous sampling methodologies so that they can provide a basis for a deeper understanding of gold-standard phylogenomic methods within a One Health context. Prospective studies should provide greater insight regarding interhost and mono-source clustering, robustly highlighting mono-source transmission dynamics, such as on-farm disease outbreaks, those in humans in clinical and community settings, or potentially provide evidence of on-farm incursion events of bacterial isolates from wildlife. Phylodynamic methods may be useful in this regard, but they require datasets with large spatiotemporal range; and accumulation of genomic surveillance data over a period of a decade or more at a national scale which may enable identification of incursion events and instances of cross-species transfer in bacterial species as has been demonstrated in viral pathogens such as for canine influenza in the United States⁵⁴.

Despite inherent sample bias, genomic clusters of closely related *E. coli* from livestock, food, humans, companion animals and/or wild animals were readily identified, providing evidence of within-host, and cross-source transmission events. Cross-source genomic clusters included pandemic zoonotic ExPEC STs, including ST131, ST95, ST69, ST117 and ST1193. Our findings emphasise the value of adopting One Health approaches to understand bacterial transmission pathways and

pathogen evolution and build towards pathogen genomic surveillance and biosecurity systems in Australia and globally.

Methods

Genome collation

We collated all available Australian *E. coli* genomes from in-house collections spanning human, companion animal, livestock, food and environmental sources from the Microbiological Diagnostic Unit Public Health Laboratory (MDU PHL) in Victoria and the Australian Centre for Genomic Epidemiological Microbiology (AusGEM) in New South Wales. The MDU PHL *E. coli* collection includes isolates referred by diagnostic laboratories for different purposes, including suspected carbapenemase-producing *E. coli* (referred for public health purposes under the Public Health and Wellbeing Act 2008, Victoria), clinical isolates submitted for extended antimicrobial susceptibility testing, and *E. coli* isolates derived from primary samples, including environmental and food isolates. All *E. coli* isolates in the collection with successful genomic sequencing (meeting quality control criteria) were included in this dataset under the University of Melbourne ethics approval (Human Research Ethics Committee Reference number: 1954615). Additionally, isolates from the 'Controlling Superbugs' study were also included in this collection (Melbourne Health HREC approval 2013.245). The Australian Centre for Genomic Epidemiological Microbiology (AusGEM) contributed strains sourced from diseased humans^{55–57}, diseased poultry^{58,59}, and companion animals³³ as well as healthy swine^{60,61} and wild birds^{38,62}. Collection of samples utilised in individual research projects was approved by respective ethics panels across collaborating institutions where required (Sydney Local Health District CRGH Human Research Ethics committee [CH62/6/2016-093 – P Chowdhury LNR/16/CRGH/120]; Elisabeth Macarthur Agricultural Institute under the Animal Ethics Committee number [M16/04]; University of New South Wales Animal Care and Ethics Committee [SL101452 14/148 A]). Pathogenic *E. coli* isolates were collected from a breadth of sample types including faecal, urinary and blood specimens from human and animal patients presenting with suspected bacterial infections. In the case of isolates from healthy animal hosts, isolation was from faecal samples and cloacal swabs. As our intention was to collate all available Australian *E. coli* genomes, selection criteria varied between collections aggregated; see individual studies for more detailed sample collection and processing methodology. We also sourced publicly available genome sequences from Enterobase⁶³ and a 2020 study by Touchon et al.⁶⁴, the latter of which was selected due to its publication of a large number of genomes that fit the study criteria. Bioproject accessions for internal collections, as well as metadata and accession numbers for all genomes under analysis, are available for all genomes in Supplementary Data 1. Genomes were required to have metadata detailing year, country, and source of isolation for inclusion.

Companion scripts

Genomic data was analysed using a custom Snakemake⁵⁵ pipeline available at <https://www.github.com/maxlcummins/pipelord> in all steps except for cgMLST and phylodynamic workflows (described below). Scripts used in the processing and visualisation of data are publicly available on Github (<https://github.com/maxlcummins/APG-OHEC-Retro-M1>). Default parameters were used unless otherwise stated.

Genome pre-processing

Read sets were filtered and trimmed using fastp v0.20.1 and assembled using Spades⁵⁶ v3.14 via shovill (www.github.com/tseeman/shovill) v1.0.4. Quality control ensured genomes exhibited: i) a length of between 3,800,000 and 6,615,000 bases using assembly-stats (<https://github.com/sanger-pathogens/assembly-stats>); ii) a known or novel multi-locus sequence type (MLST) of *E. coli* (Achtman scheme) (www.github.com/tseeman/mlst, v2.19.0); iii) 50% of sequence reads

mapping to *E. coli* using Kraken2⁵⁷ v2.1.2 (parameter: ‘--db bacteria’) and Bracken⁵⁸ v2.5; iv) less than 10% contamination and greater than 90% completeness scores using CheckM⁵⁹ v1.2.0. Isolates were also required to have 95% of 2,513 cgMLST alleles present to be considered for further analysis.

Phylogenetic analysis

Core-genome multilocus sequence types (cgMLSTs) were generated using chewBBACA⁶⁰ v2.8.5 (cgMLST schema <https://enterobase.warwick.ac.uk/schemes/Escherichia.cgMLSTv1> - accessed 19/07/2022) via the wrapper Coreugate (<https://github.com/MDU-PHL/Coreugate>) v2.0.5, the latter generated pairwise allelic distances and a phylogenetic tree using rapidNJ⁶¹ v2.3.3 using default settings. When ≥ 2 isolates exhibited an allelic distance ≤ 40 , they were considered putative genomic clusters. Consensus on appropriate thresholds for One Health microbial genomic epidemiology are lacking, however a threshold of ≤ 100 allelic distances has been used for preliminary clustering in other research exploring One Health transmission events²⁶. We opted for a more conservative threshold of ≤ 40 to minimise high-resolution comparison of genomes differing by large numbers of SNPs. Due to the volume of genomic data under analysis, this preliminary screening step reduced the need for an “all vs all”, high-resolution phylogenetic analysis, allowing us to focus our efforts (and computational processing power) on a subset of genomes of interest. We also performed an additional preliminary clustering analysis using PopPunk²³ v2.67 using default settings and the v2 *E. coli* database (available at https://ftp.ebi.ac.uk/pub/databases/pp_dbs/escherichia_coli_v2_full.tar.bz2).

Subsequent, high-resolution phylogenetic analyses on a subset of 10 STs most commonly associated with putative genomic clusters, on a ST-wise basis, was performed using Split Kmer Analysis (SKA)⁶² v1.0, with two or more strains differing by ≤ 100 SNPs considered a genomic cluster and any individual two strains meeting this criteria being classified as a clustering pair. This threshold was chosen after a thorough search of the literature; few studies have assessed one health transmission as opposed to direct transmission, and there was little concordance in examining cross sectoral relationships within *E. coli*. Thresholds ranged from 15 to 100 SNPs with clonality considered up to 200 + SNPs^{63–67}. As the aim of this study was to examine One Health genomic clusters and not direct transmission, a threshold of ≤ 100 SNPs was chosen.

A core-genome alignment was generated for ST131, ST1193 and ST95 using snippy⁶⁸ v4.4.3 and a maximum-likelihood tree was built using IQ-Tree⁶⁹ v2.0.3 (parameters: ‘-m GTR+F -bb 1000’). These sequence types were selected for analysis given their relatively high frequency and implication with cross-source genomic clusters. Core genomic alignments for the three sequence types (STs) were assessed, in combination with their collection years, for temporal structure (i.e., clock-like mutation rates) using both TempEst⁷⁰ v1.5.3 and Bayesian Evaluation of Temporal Signal (BETS)⁷¹. Phylogroups were assigned using Clermontyper⁷² v2.0.3.

Statistical analysis and visualisation

Statistical analyses were performed using R version 4.0.2. Packages utilised for statistical analysis and general processing and visualisation in R include: igraph v2.0.3⁷³, tidyverse⁷⁴ v2.0.0, ggplot2⁷⁵ v3.4.4, ggrepel⁷⁶ v0.9.3, ggalluvial⁷⁷ v0.12.5, ggvenn⁷⁸ v0.1.10, plotly⁷⁹ v4.10.2, caret⁸⁰ v6.0-94, pheatmap⁸¹ v1.0.12, circlize⁸² v0.4.15, and scales⁸³ v1.3.0. Non-parametric correlation analyses for SNP and cgMLST distances were performed using the Spearman Correlation coefficient via ggpubr⁸⁴ v0.6.0. Cluster metrics, including Silhouette, Calinski-Harabasz, Davies-Bouldin, Within-Cluster Sum of Squares, Cohesion, and Separation, were used to analyse SNP cutoff thresholds. The analysis was performed in Python version 3.10.12 using sklearn⁸⁵ v1.2.2, scipy⁸⁶ v1.11.4, and networkx⁸⁷ v3.3. The change in each cluster

metric due to different cut-off thresholds was statistically assessed using a permutation test with 1000 iterations.

Ethics

Ethical approval was received from the Royal Melbourne Hospital Human Research Ethics Committee (study number RMH83761). All authors verify the integrity and completeness of data and analyses.

Reporting summary

Further information on research design is available in the Nature Portfolio Reporting Summary linked to this article.

Data availability

Metadata and accession numbers are available for all genomes in Supplementary Data 1.

Code availability

Scripts used in the processing and visualisation of data are publicly available on Github⁸⁸ (<https://github.com/maxcummins/APG-OHEC-Retro-M1>), as are pipelines used for genomic analysis⁸⁹ (<https://github.com/maxcummins/pipelord>).

References

- Djordjevic, S. P. et al. Genomic surveillance for antimicrobial resistance—a One Health perspective. *Nat. Rev. Genet.* **25**, 142–157 (2024).
- Adisasmito, W. B. et al. One Health: A new definition for a sustainable and healthy future. *PLoS Pathog.* **18**, e1010537 (2022).
- Dubreuil, J. D., Isaacson, R. E. & Schifferli, D. M. Animal Enterotoxigenic *Escherichia coli*. *EcoSal Plus* **7**, <https://doi.org/10.1128/ecosalplus.ESP-0006-2016> (2016).
- Nagy, B. & Fekete, P. Z. Enterotoxigenic *Escherichia coli* in veterinary medicine. *Int. J. Med. Microbiol.* **295**, 443–454 (2005).
- Nagy, B. & Fekete, P. Z. Enterotoxigenic *Escherichia coli* (ETEC) in farm animals. *Vet. Res* **30**, 259–284 (1999).
- Rollin, E., Dhuyvetter, K. C. & Overton, M. W. The cost of clinical mastitis in the first 30 days of lactation: An economic modeling tool. *Preventive Vet. Med.* **122**, 257–264 (2015).
- Blum, S. E. et al. Postgenomics characterization of an essential genetic determinant of mammary pathogenic *Escherichia coli*. *mBio* **9**, e00423–00418 (2018).
- Rizzo, D. M., Lichtveld, M., Mazet, J. A., Togami, E. & Miller, S. A. Plant health and its effects on food safety and security in a one health framework: four case studies. *One health outlook* **3**, 6 (2021).
- Aijuka, M. & Buys, E. M. Persistence of foodborne diarrheagenic *Escherichia coli* in the agricultural and food production environment: implications for food safety and public health. *Food Microbiol.* **82**, 363–370 (2019).
- García, A., Fox, J. G. & Besser, T. E. Zoonotic enterohemorrhagic *Escherichia coli*: a one health perspective. *ILAR J.* **51**, 221–232 (2010).
- Griffin, P. M. & Karmali, M. A. Emerging public health challenges of shiga toxin-producing *Escherichia coli* related to changes in the pathogen, the population, and the environment. *Clin. Infect. Dis.* **64**, 371–376 (2016).
- Torres, A. G. *Escherichia coli* diseases in Latin America—a ‘One Health’ multidisciplinary approach. *Pathogens and Disease* **75**, <https://doi.org/10.1093/femspd/ftx012> (2017).
- Yu, D., Ryu, K., Zhi, S., Otto, S. J. & Neumann, N. F. Naturalized *Escherichia coli* in wastewater and the co-evolution of bacterial resistance to water treatment and antibiotics. *Front. Microbiol.* **13**, 810312 (2022).
- Seemann, T. et al. Tracking the COVID-19 pandemic in Australia using genomics. *Nat. Commun.* **11**, <https://doi.org/10.1038/s41467-020-18314-x> (2020).

15. Sherry, N. L. et al. Genomics for molecular epidemiology and detecting transmission of carbapenemase-producing enterobacteriales in Victoria, Australia, 2012 to 2016. *J. Clin. Microbiol.* **57**, e00573–00519 (2019).
16. Harris, S. R. et al. Whole-genome sequencing for analysis of an outbreak of methicillin-resistant *Staphylococcus aureus*: a descriptive study. *Lancet Infect. Dis.* **13**, 130–136 (2013).
17. Milenkov, M. et al. Implementation of the WHO Tricycle protocol for surveillance of extended-spectrum β -lactamase producing *Escherichia coli* in humans, chickens, and the environment in Madagascar: a prospective genomic epidemiology study. *Lancet Microbe*. **5**, 100850 (2024).
18. Leeper, M. M. et al. Evaluation of whole and core genome multilocus sequence typing allele schemes for *Salmonella enterica* outbreak detection in a national surveillance network, PulseNet USA. *Front. Microbiol.* **14**, 1254777 (2023).
19. Blanc, D. S., Magalhães, B., Koenig, I., Senn, L. & Grandbastien, B. Comparison of whole genome (wg-) and core genome (cg-) MLST (BioNumerics™) versus SNP variant calling for epidemiological investigation of *Pseudomonas aeruginosa*. *Front. Microbiol.* **11**, 1729 (2020).
20. Miro, E. et al. Core/whole genome multilocus sequence typing and core genome SNP-based typing of OXA-48-producing *Klebsiella pneumoniae* clinical isolates from Spain. *Front. Microbiol.* **10**, 495333 (2020).
21. Mohammed, M. & Thapa, S. Evaluation of WGS-subtyping methods for epidemiological surveillance of foodborne salmonellosis. *One Health Outlook* **2**, 1–15 (2020).
22. Wang, Y. Y. et al. Application of a core genome sequence typing (cgMLST) pipeline for surveillance of *Clostridioides difficile* in China. *Front. Cell. Infect. Microbiol.* **13**, 1109153 (2023).
23. Lees, J. A. et al. Fast and flexible bacterial genomic epidemiology with PopPUNK. *Genome Res.* **29**, 304–316 (2019).
24. Cummins, M. L., Reid, C. J. & Djordjevic, S. P. F plasmid lineages in *Escherichia coli* ST95: implications for host range, antibiotic resistance, and zoonoses. *Msystems* **7**, e01212–01221 (2022).
25. Murray, C. J. et al. Global burden of bacterial antimicrobial resistance in 2019: a systematic analysis. *Lancet* **399**, 629–655 (2022).
26. Muloi, D. M. et al. Genomic epidemiology of *Escherichia coli*: antimicrobial resistance through a one health lens in sympatric humans, livestock and peri-domestic wildlife in Nairobi, Kenya. *BMC Med.* **20**, 471 (2022).
27. Zhi, S. et al. Evidence for the evolution, clonal expansion and global dissemination of water treatment-resistant naturalized strains of *Escherichia coli* in wastewater. *Water Res.* **156**, 208–222 (2019).
28. Davies, J. & Davies, D. Origins and evolution of antibiotic resistance. *Microbiol. Mol. Biol. Rev.* **74**, 417–433 (2010).
29. Gorrie, C. L. et al. Key parameters for genomics-based real-time detection and tracking of multidrug-resistant bacteria: a systematic analysis. *Lancet Microbe* **2**, e575–e583 (2021).
30. Murphy, R. et al. Genomic epidemiology and evolution of *Escherichia coli* in wild animals in Mexico. *Msphere* **6**, 00738–00720 (2021).
31. Lupolova, N., Lycett, S. J. & Gally, D. L. A guide to machine learning for bacterial host attribution using genome sequence data. *Microb. Genomics* **5**, e000317 (2019).
32. Riley, L. Pandemic lineages of extraintestinal pathogenic *Escherichia coli*. *Clin. Microbiol. Infect.* **20**, 380–390 (2014).
33. Elankumaran, P. et al. Genomic and temporal trends in canine ExPEC reflect those of human ExPEC. *Microbiol. Spectr.* **10**, e01291–01222 (2022).
34. Wagner, S., Gally, D. L. & Argyle, S. A. Multidrug-resistant *Escherichia coli* from canine urinary tract infections tend to have commensal phylotypes, lower prevalence of virulence determinants and ampC-replicons. *Vet. Microbiol.* **169**, 171–178 (2014).
35. LeCuyer, T. E. et al. Population structure and antimicrobial resistance of canine uropathogenic *Escherichia coli*. *J. Clin. Microbiol.* **56**, 00788–00718 (2018).
36. Kathayat, D., Lokesh, D., Ranjit, S. & Rajashekara, G. Avian pathogenic *Escherichia coli* (APEC): an overview of virulence and pathogenesis factors, zoonotic potential, and control strategies. *Pathogens* **10**, 467 (2021).
37. Nicolas-Chanoine, M.-H., Bertrand, X. & Madec, J.-Y. *Escherichia coli* ST131, an intriguing clonal group. *Clin. Microbiol. Rev.* **27**, 543–574 (2014).
38. Medvecky, M. et al. Interspecies transmission of CMY-2-producing *Escherichia coli* sequence type 963 isolates between humans and gulls in Australia. *Msphere* **7**, e00238–00222 (2022).
39. Xia, F. et al. Complete genomic analysis of ST117 lineage extraintestinal pathogenic *Escherichia coli* (ExPEC) to reveal multiple genetic determinants to drive its global transmission: ST117 *E. coli* as an emerging multidrug-resistant foodborne ExPEC with zoonotic potential. *Transbound. Emerg. Dis.* **69**, 3256–3273 (2022).
40. Wyrsh, E. R., Bushell, R. N., Marena, M. S., Browning, G. F. & Djordjevic, S. P. Global phylogeny and F virulence plasmid carriage in pandemic *Escherichia coli* ST1193. *Microbiol. Spectr.* **10**, e02554–02522 (2022).
41. Hochmuth, G., Hochmuth, R. & Mylavarapu, R. Using composted poultry manure (Litter) in mulched vegetable production: SL 293/SS506, 10/2009. *EDIS* **2009**, (2009).
42. Elankumaran, P., Browning, G. F., Marena, M. S., Reid, C. J. & Djordjevic, S. P. Close genetic linkage between human and companion animal extraintestinal pathogenic *Escherichia coli* ST127. *Curr. Res. Microb. Sci.* **3**, 100106 (2022).
43. Elankumaran, P. et al. Identification of genes influencing the evolution of *Escherichia coli* ST372 in dogs and humans. *Microb. Genomics* **9**, 000930 (2023).
44. Aurich, S. et al. Genotypic characterization of uropathogenic *Escherichia coli* from companion animals: predominance of ST372 in dogs and human-related ST73 in cats. *Antibiotics* **13**, 38 (2023).
45. Damborg, P., Pirolo, M., Schøn Poulsen, L., Frimodt-Møller, N. & Guardabassi, L. Dogs can be reservoirs of *Escherichia coli* strains causing urinary tract infection in human household contacts. *Antibiotics* **12**, 1269 (2023).
46. Ewers, C. et al. Emergence of human pandemic O25: H4-ST131CTX-M-15 extended-spectrum- β -lactamase-producing *Escherichia coli* among companion animals. *J. antimicrobial Chemother.* **65**, 651–660 (2010).
47. Li, D. et al. Genomic comparisons of *Escherichia coli* ST131 from Australia. *Microb. Genomics* **7**, 000721 (2021).
48. Cummins, M. L. et al. Whole-genome sequence analysis of an extensively drug-resistant *Salmonella enterica* serovar Agona isolate from an Australian silver gull (*Chroicocephalus novae-hollandiae*) reveals the acquisition of multidrug resistance plasmids. *Msphere* **5**, 00743–00720 (2020).
49. Freeman, M. T., Czenze, Z. J., Schoeman, K. & McKechnie, A. E. Adaptive variation in the upper limits of avian body temperature. *Proc. Natl Acad. Sci.* **119**, e2116645119 (2022).
50. Crane, J. K., Alvarado, C. L. & Sutton, M. D. Role of the SOS response in the generation of antibiotic resistance in vivo. *Antimicrobial Agents Chemother.* **65**, 00013–00021 (2021).
51. Beaber, J. W., Hochhut, B. & Waldor, M. K. SOS response promotes horizontal dissemination of antibiotic resistance genes. *Nature* **427**, 72–74 (2004).
52. Baharoglu, Z., Bikard, D. & Mazel, D. Conjugative DNA transfer induces the bacterial SOS response and promotes antibiotic resistance development through integron activation. *PLoS Genet.* **6**, e1001165 (2010).

53. Maharjan, R. P. & Ferenci, T. Escherichia coli mutation rates and spectra with combinations of environmental limitations. *Microbiology* **164**, 1491–1502 (2018).
54. Voorhees, I. E. et al. Multiple incursions and recurrent epidemic fade-out of H3N2 canine influenza virus in the United States. *J. Virol.* **92**, 00323–00318 (2018).
55. Köster, J. & Rahmann, S. Snakemake—a scalable bioinformatics workflow engine. *Bioinformatics* **28**, 2520–2522 (2012).
56. Bankevich, A. et al. SPAdes: a new genome assembly algorithm and its applications to single-cell sequencing. *J. computational Biol.* **19**, 455–477 (2012).
57. Wood, D. E. & Salzberg, S. L. Kraken: ultrafast metagenomic sequence classification using exact alignments. *Genome Biol.* **15**, 1–12 (2014).
58. Lu, J., Breitwieser, F. P., Thielen, P. & Salzberg, S. L. Bracken: estimating species abundance in metagenomics data. *PeerJ Computer Sci.* **3**, e104 (2017).
59. Parks, D. H., Imelfort, M., Skennerton, C. T., Hugenholtz, P. & Tyson, G. W. CheckM: assessing the quality of microbial genomes recovered from isolates, single cells, and metagenomes. *Genome Res.* **25**, 1043–1055 (2015).
60. Silva, M. et al. chewBBACA: A complete suite for gene-by-gene schema creation and strain identification. *Microb. genomics* **4**, e000166 (2018).
61. Simonsen, M., Mailund, T. & Pedersen, C. N. In *Algorithms in Bioinformatics: 8th International Workshop, WABI 2008, Karlsruhe, Germany September 15–19, 2008. Proceedings 8*, 113–122 (Springer, 2008).
62. Harris, S. R. SKA: split kmer analysis toolkit for bacterial genomic epidemiology. *BioRxiv*, 453142 (2018).
63. Milenkov, M. et al. *Tricycle surveillance in Antananarivo, Madagascar: circulation of both extended-spectrum beta-lactamase producing Escherichia coli strains and plasmids among humans, chickens and the environment* (Cold Spring Harbor Laboratory, 2023).
64. Ludden, C. et al. One health genomic surveillance of Escherichia coli demonstrates distinct lineages and mobile genetic elements in isolates from humans versus livestock. *mBio* **10**, e02693–02618 (2019).
65. Montealegre, M. C. et al. High genomic diversity and heterogeneous origins of pathogenic and antibiotic-resistant Escherichia coli in household settings represent a challenge to reducing transmission in low-income settings. *mSphere* **5**, e00704–00719 (2020).
66. Nesporova, K. et al. Escherichia coli Sequence Type 457 Is an Emerging Extended-Spectrum-β-Lactam-Resistant Lineage with Reservoirs in Wildlife and Food-Producing Animals. *Antimicrob Agents Chemother* **65**, <https://doi.org/10.1128/aac.01118-20> (2020).
67. Salinas, L. et al. Environmental spread of extended spectrum beta-lactamase (ESBL) Producing Escherichia coli and ESBL Genes among children and domestic animals in Ecuador. *Environ. Health Perspect.* **129**, 27007 (2021).
68. snippy: fast bacterial variant calling from NGS reads (<https://github.com/tseemann/snippy>, 2015).
69. Nguyen, L.-T., Schmidt, H. A., Von Haeseler, A. & Minh, B. Q. IQ-TREE: a fast and effective stochastic algorithm for estimating maximum-likelihood phylogenies. *Mol. Biol. evolution* **32**, 268–274 (2015).
70. Rambaut, A., Lam, T. T., Max Carvalho, L. & Pybus, O. G. Exploring the temporal structure of heterochronous sequences using TempEst (formerly Path-O-Gen). *Virus evolution* **2**, vew007 (2016).
71. Duchene, S. et al. Bayesian evaluation of temporal signal in measurably evolving populations. *Mol. Biol. Evolution* **37**, 3363–3379 (2020).
72. Beghain, J., Bridier-Nahmias, A., Le Nagard, H., Denamur, E. & Clermont, O. ClermonTyping: an easy-to-use and accurate in silico method for Escherichia genus strain phylotyping. *Microb. genomics* **4**, e000192 (2018).
73. Csardi, G. & Nepusz, T. The igraph software. *Complex syst.* **1695**, 1–9 (2006).
74. Wickham, H. et al. Welcome to the Tidyverse. *J. open source Softw.* **4**, 1686 (2019).
75. Villanueva, R. A. M., & Chen, Z. J. ggplot2: Elegant Graphics for Data Analysis (2nd ed.). Measurement: Interdisciplinary Research and Perspectives, **17**, 160–167 (2019).
76. Slowikowski, K. et al. Package ggrepel. *Automatically position non-overlapping text labels with 'ggplot2'* (2018).
77. Brunson, J. C. Ggalluvial: layered grammar for alluvial plots. *J. Open Source Softw.* **5**, 2017 (2020).
78. Gao, C.-H., Yu, G. & Cai, P. ggVennDiagram: an intuitive, easy-to-use, and highly customizable R package to generate Venn diagram. *Front. Genet.* **12**, 706907 (2021).
79. Sievert, C. *Interactive web-based data visualization with R, plotly, and shiny*. (Chapman and Hall/CRC, 2020).
80. Kuhn, M. Building predictive models in R using the caret package. *J. Stat. Softw.* **28**, 1–26 (2008).
81. Kolde, R. & Kolde, M. R. Package 'pheatmap'. *R. package* **1**, 790 (2015).
82. Gu, Z., Gu, L., Eils, R., Schlesner, M. & Brors, B. “Circize” implements and enhances circular visualization in R. (2014).
83. Wickham, H. & Seidel, D. scales: scale functions for visualization. *R. package version* **1**, 1 (2020).
84. Kassambara, A. & Kassambara, M. A. Package 'ggpubr'. *R package version* **0.1.6** (2020).
85. Pedregosa, F. et al. Scikit-learn: Machine Learning in Python. *J. Mach. Learn. Res.* **12**, 2825–2830 (2011).
86. Virtanen, P. et al. SciPy 1.0: fundamental algorithms for scientific computing in Python. *Nat. Methods* **17**, 261–272 (2020).
87. Hagberg, A., Schult, D. & Swart, P. In *Proceedings of the 7th Python in Science conference*. (eds G. Varoquaux, T. et al. SciPy 2008).
88. Cummins, M.L. <https://github.com/maxlcummins/APG-OHEC-Retro-M1> (2024).
89. Cummins, M.L. maxlcummins/pipelord: Nature Comms Publication (v1.0.0). Zenodo. <https://doi.org/10.5281/zenodo.14048334> (2024).

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Author contributions

B.H., S.D., A.W., M.C. designed the project. BH and SD secured funding. W.W., P.A., C.D., E.D., T.S. and A.J. contributed to project design and analytical approaches. A.W., M.C., T.S., W.W. and A.P. analysed the data. B.H. and S.D. provided data. A.W. and M.C. drafted the manuscript with C.D., S.D. and B.H. All authors reviewed and approved the manuscript.

Competing interests

The authors declare that there are no conflicts of interest regarding the generation and publication of this manuscript.

Additional information

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Australian Pathogen Genomics One Health Working Group

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