

The urinary tract microbiome in older women exhibits host genetics and environmental influences

AS Adebayo¹, G Ackermann², RC Bowyer¹, P Wells¹, G Humphreys², R Knight², TD Spector¹, CJ Steves^{1*}

¹Department of Twin Research & Genetic Epidemiology, King's College London, United Kingdom ; ²The Knight Lab, Paediatrics, University of California San Diego, United States

*Corresponding author/Lead Contact: claire.j.steves@kcl.ac.uk

Summary

The urinary microbiome is a relatively unexplored niche despite the fact that we now know that it is not sterile. Moreover urinary microbes, especially in ageing populations, are associated with morbidity even when infection is subsequently not proven. We present the first large-scale study to explore factors defining urinary microbiome composition in community-dwelling older adult women without clinically active infection. Using 1600 twins, we estimate the contribution of genetic and environmental factors to variation in microbiome using both 16S and shotgun metagenomics. We found that the urinary microbiome is distinct from nearby sites and is unrelated to stool microbiome. Core urinary microbiome taxa were defined. The first component of weighted unifracs was heritable (18%) as were key taxa (e.g. *Escherichia-Shigella* ($A > 0.15$)). Age, menopausal status, prior UTI and host genetics were top among factors defining the urobiome. Increased composition was associated with older age, contrary to previous findings.

Keywords: microbiome, genetics, urogenital tract, ageing

Introduction

The resident microbial community (microbiome) at different human body sites, continues to generate research interest, driven by evidence of a role in human physiology. The study of the urinary microbiome (urobiome) is much less established compared to the gut microbiome; perhaps due to the previous belief that the urine was sterile in the absence of a urinary tract infection. Recently, research has shown that this is not the case and that the urinary tract is in fact, another site with a microbiome, reflective of the microbes inhabiting the bladder and closely associated organs (Wolfe et al., 2012; Siddiqui et al., 2012; Whiteside et al., 2015). This evidence is supported

37 by enhanced quantitative cultures, 16S marker studies and metagenomics, in different
38 populations (e.g Kramer et al., 2018; Adebayo et al., 2017; Wu et al., 2017).

39

40 Studies to date have identified differences in the urobiome in relation to urinary tract
41 conditions (Sihra et al., 2018; Wolfe & Brubaker, 2019) including urinary infections
42 (UTI). There is evidence for sex differences in the urinary microbiome which may in
43 part be due to differences in the length of the urinary tract (Moustafa et al. 2018).

44 Women are much more likely to develop UTI, with a lifetime risk of up to 50%
45 (Franco, 2005). UTI is also the commonest reason for antibiotic treatment in adult
46 women, which has implications for urinary and other microbiomes and antimicrobial
47 resistance. Early work has indicated that the non-infected state microbiome may
48 influence resilience to infection. Thus this paper is focused on understanding the
49 major factors defining the urobiome in community dwelling women without active
50 infection.

51 Recent studies involving urinary/bladder microbiomes have involved relatively small
52 sample sizes (dozens or few hundreds of people) in hospital or clinic attending
53 patients. For instance, results from our literature search (Jan 2015 to September 2018)
54 included case-control studies on elderly/non-elderly patients (Liu et al., 2017; n=100);
55 urinary tract infections (Moustafa et al., 2018; n=112), cancer (Wang et al., 2017;
56 n=65), diabetes, overactive bladder (Wu et al., 2017; Fok et al., 2018,; n=55-126),
57 chronic kidney disease (Kramer et al, 2018; n=41); surgical transplant patients (Rani
58 et al., 2018, n=20); menopause (Curtiss et al., 2018; n=78). Reinforcing this, a recent
59 review (covering studies up to 2016) carried out by Aragon et al. (2018) reported that
60 the sample sizes in urinary microbiome studies varied between 8 to 60 for healthy
61 controls and 10-197 for cases. Their report shows that many studies are
62 commissioned on incontinence, bladder-related and gynaecologic patients. Moreover,
63 many of the urine microbiome studies, either with 16S or shotgun metagenomes,
64 exclude samples with non-detectable/ below detection microbiome. While the
65 assumption maybe that the failure is completely technical, it is unknown if host
66 factors contribute to having 'extremely-low' or 'below detection' urine microbiome.

67 Recently, studies of the gut microbiome, have shown a role of host genetics. While
68 Goodrich and colleagues first reported clearly heritable components within the gut

69 microbiome (Goodrich et al.,2014), a finding which a few subsequent studies have
70 also reiterated(Luca et al., 2018), Rothchilds et al reported that environmental factors
71 may largely blur such host genetics factors (Rothchilds et al.,2018). It is unknown if
72 genetic factors are important in the urinary microbiome.

73 We aimed to characterize the host influence on the urinary tract microbiome in
74 women. Using midstream urine samples from 1600 females in the TwinsUK cohort,
75 this study, perhaps the largest on urinary microbiome so far, reports about the urinary
76 microbiome composition in an average female population of mainly postmenopausal
77 women with no apparent infection. We hypothesized that, in an unselected average
78 population, (1) the inherent core urinary bacterial community could be defined (2)
79 that the urobiome is influenced by host-specific genetic and environmental factors, (3)
80 that some host-specific factors may relate to undetectable microbial biomass in the
81 urine.

82

83 **Results**

84 Urinary microbiome across studies and were distinct from proximal body sites and 85 shared key taxa

86 Initially, we compared the overall composition of the urinary microbiome to similar
87 datasets from other body sites using the same bioinformatics pipeline, using similar
88 sized datasets of women aged >45(Supplementary Methods & Data1). Alpha diversity
89 in the urine was, on average, reduced relative to the stool and is comparable in two
90 urine and the vaginal datasets (Fig 1A). Stool samples in the majority ordinated
91 separately from urine samples (Fig 1B) (Supplementary Data 1). Repeating these
92 diversity analyses with a separate set of random 100 samples each show similar
93 patterns and significance (SFig1A,B). In paired-sample analysis from TwinsUK
94 (Supplementary Data1), urine microbial taxa separated from stool microbial taxa of
95 the same individual (S1C). There was no clear correlation in the pattern of stool and
96 urine microbiome dissimilarity for the paired samples (either obtained at same time
97 point or not) (Mantel's $r \leq 0.02$, $p > 0.1$) and variance was not homogeneous (Levene
98 paired test $p = 0.02$) (Fig 1C-D, SData1). Thereafter, we examined the TwinsUK
99 urinary microbiome dataset alone.

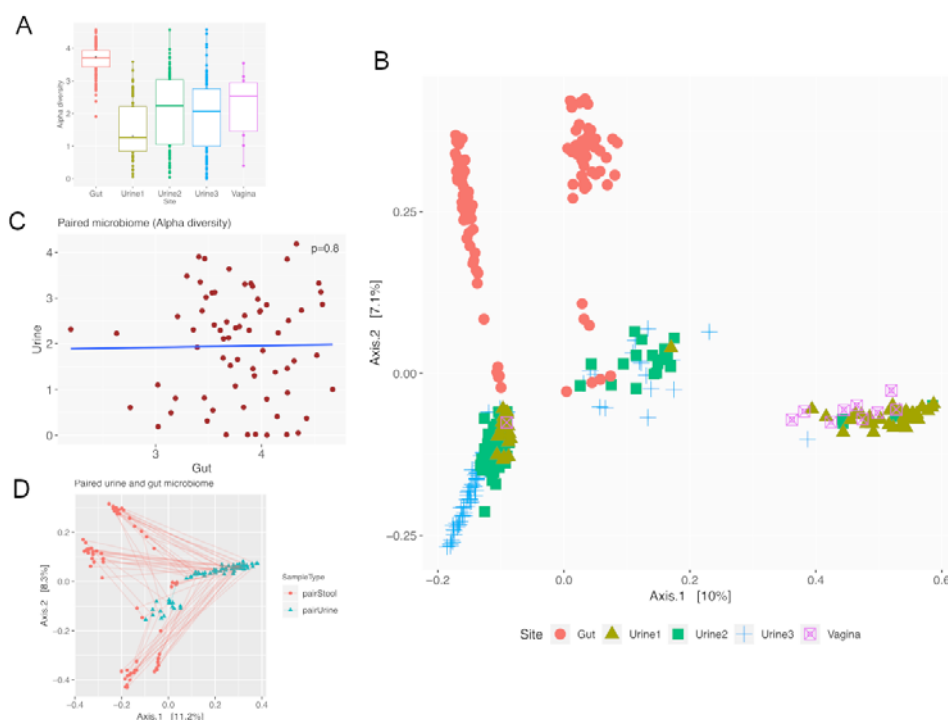


Fig 1. Urinary microbiome in older women is mostly distinct from proximal body sites and unrelated to stool microbiome. (A) Alpha diversity of urine microbiomes and other body sites. star symbol indicates significance compared to TwinsUK urobiome. (B) Dissimilarities in urine microbiomes and other body sites. Plots are based on unifracs distances (C) Paired alpha diversity analysis of stool and urine collected at same time point (D) Differences in paired stool and urine microbiome from the same time point.

General description of urobiome

Urine samples from 1600 mainly postmenopausal women (mean age 66.4) in the TwinsUK cohort were analysed, revealing 10955 present species-level taxa from filtered 16S data. Participant characteristics are shown in Table 1. There was high level of variability in particular species present in an individual, with only 246 (2.2%) ASVs occurring in at least 5% of samples. The use of a compositionally-sensitive analysis improved the ranking of some abundant taxa as compared to common non-compositional analysis (SFig3). To highlight intra-microbiome relationships, hierarchical balances were created, resulting in mixed-genera subclusters from 61 species-level taxa (hereafter referred to as the core urobiome). There were more Actinobacteria, Fusobacteria and Proteobacteria compared to normal gut microbiome (SFig 3B).

120 Having low reads (no reliably-detected microbiome (<2000 reads post-filtering))
 121 (Supplementary Data 2) associated with younger age and lower level of health deficit;
 122 specifically, a ~20% increase in the chances of detectable microbiome for a unit
 123 increase in age ($p=0.0048$, $OR=1.21$, $CI=1.07 - 1.39$) and ~14% increase for a unit
 124 increase in the frailty index ($OR=1.144$, $CI=1.01-1.30$, $p=0.0359$). There was no
 125 association between low read status and the number of previous Urinary Tract
 126 Infections (UTIs), recent antibiotics usage, surgery episodes or number of childbirth
 127 episodes (parity); amplicon concentrations associated with parity ($\beta=1.89$, $p=0.0035$)
 128 alone among other demographics (Supplementary Data 2).

129

130 Host genetics' influences variation of urine microbiome

131 First, the quantitative twin model analysis showed considerable and significant
 132 genetic component in the first principal coordinate (PCo) of beta diversity (inter-
 133 individual) distances which capturing 57% of the variation. Heritability of this first
 134 PCo was 18% ($A=0.179$, $CI=0.05-0.415$, $p=0.003351$; $C=0.0049$, $E=0.8164$, $n=760$
 135 pairs) (Fig2A). Significant heritability was maintained when adjusting for other
 136 factors (Supplementary Data 3). Likewise, treating the microbiome data as Atchinson
 137 composition, the first principal component (63% of variation) on inter-sample
 138 distances showed 21% heritability ($CI=0.10-0.32$, $C=0.00$, $E=0.79$), and the first PC
 139 was also associated with genetic relatedness (family identity) (Kruskal-Wallis
 140 $p=0.043$). Some clusters showed higher heritability (Fig 2B).

141

142 In addition, the dissimilarity within relatives (twin pair) in constrained principal
 143 coordinates analysis and the average difference in Euclidean distances to the normal
 144 PCo median were both smaller for monozygotic pairs ($p \leq 0.027$) (Fig2C and Fig 3D)
 145 (Supplementary Data 3), providing further evidence of a genetic component. While
 146 the study population was majorly of British ancestry, and therefore ethnicity findings
 147 would need to be confirmed, the second PCo of the microbiome diversity differed
 148 according to the 4 major ancestry or ethnic origins present (1st PC; $p=0.156$; 2nd PC
 149 $p=0.000143$), as was the Bray-Curtis dissimilarity between the ancestry groups
 150 (Supplementary Data 3, Fig. 2D).

151

152 Moreover, the common urobiome taxa (using balance transformations) showed
 153 heritability of 23% (95% $CI=8.77$ to 33.7 , $C=1.66E-12$). Almost a quarter (59 of 245)

of frequent species had heritability greater than 10%, and some of the most heritable species (e.g. *Lactobacillus iners* AB-1 and *Escherchia-Shigella* sp.) clustered together and members showed phylogenetic relatedness among themselves and with *Christenellaceae* species (SFig 1D-E). Because of the potential role of some of these heritable species in UTIs, we also tested the heritability of occurrence of prior urinary tract infections, finding prior UTI to be significantly heritable ($A=0.273$, 95%CI=0.178 – 0.368, $p=3.073E-13$, see Supplementary Data 3) possibly up to 40%.

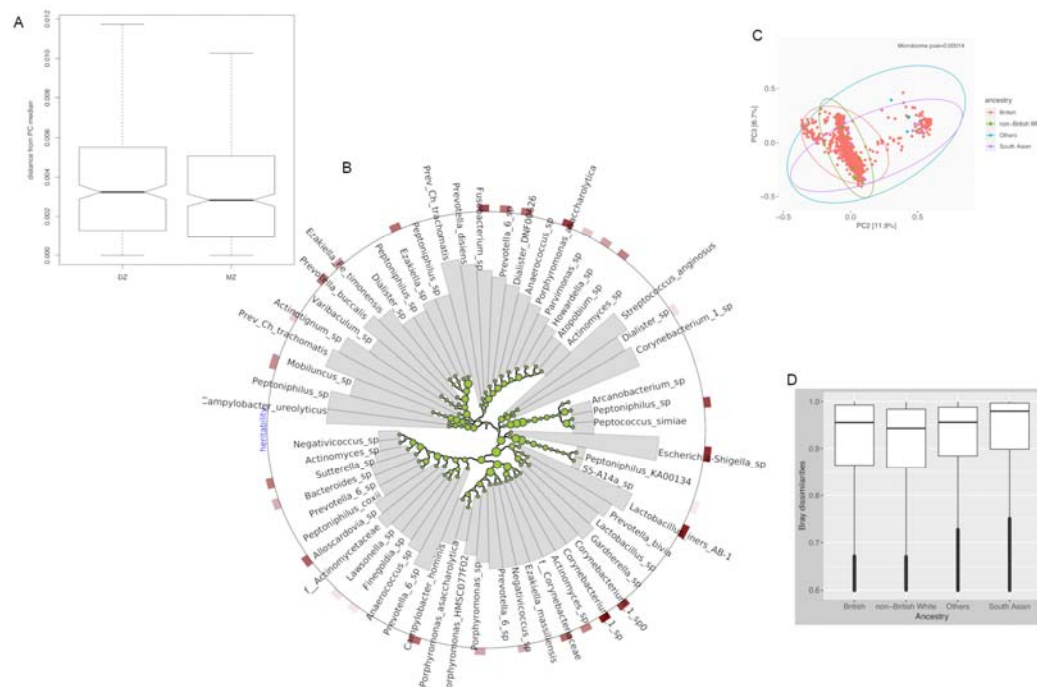


Fig 2. Host genetics considerably influences variation of urine microbiome. (A) Discordance in paired twin types for Euclidean distances to median microbiome in PC. MZ-monozygotic pair; DZ:Dizygotic pair; PC: principal coordinate (B). Heritability and interaction of core urinary microbes. Size of circles at each subcluster and intensity of rectangular bars at the tips represent increasing heritability of taxa. Neighbouring species in a clade show co-abundance. Taxa are annotated to indicate different species. Clusters are not phylogenetic. (D). **Microbiome principal coordinates with ancestral origin.** White British constitute >90% of individuals. P-values are derived from permutational models due to imbalanced sizes. Ellipses represent 95% confidence interval. (E) **Bray dissimilarities with the ethnic or ancestry divisions.**

175

176

177 Host-related/environmental factors in urinary microbiome, especially age, have
178 important effects

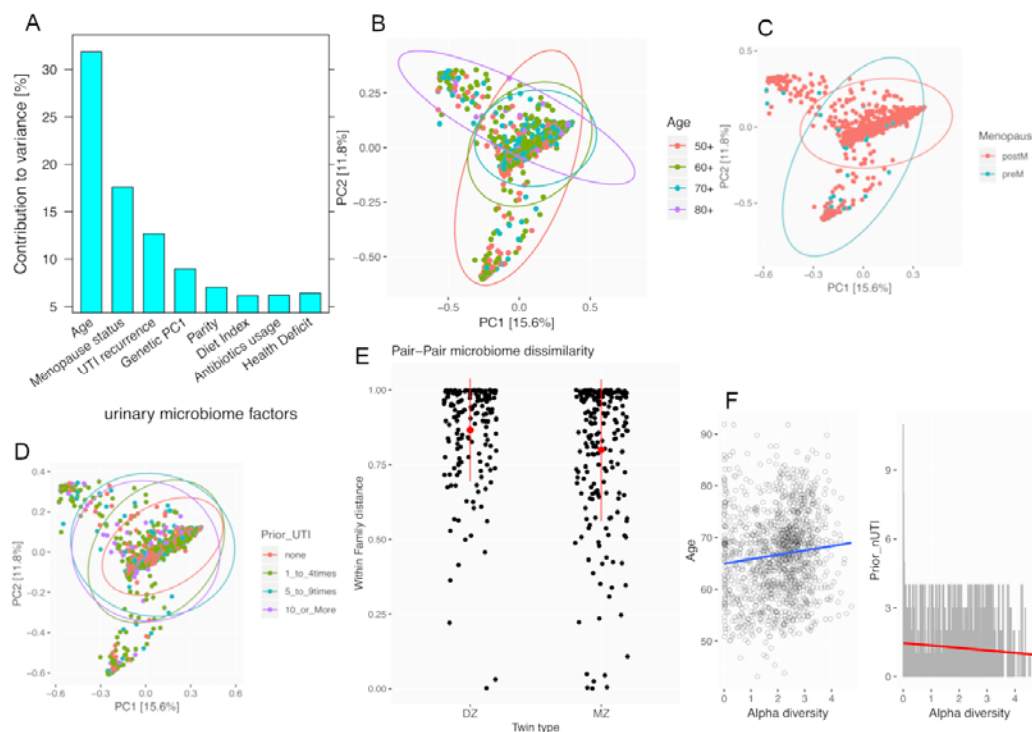
179 Age, diet, recent antibiotic usage and overall health deficit were assessed in relation to
180 the urobiome as they are known ‘host-specific’ influencers of gut microbiome
181 variation. Parity (previous number of births) and surgical history (had previous
182 surgery or not) were assessed as host-related “environmental” factors as they could
183 potentially alter structures in or proximal to the urinary tract. Previous history of UTI
184 was also assessed.

185 With increasing age, there is overall increase in alpha diversity (Table 1), which was
186 robust to uneven sample sizes or exclusion of small number of participants aged <50
187 ($0.10 \geq \beta \leq 0.22$, $0.00027 \leq p \leq 0.0045$). Age differed with beta diversity estimates
188 ($p < 0.001$), and was a main influencer of the 3 ‘enterotypes’ (directions) visible in the
189 PCo plot (Fig 2B). The core urobiome and one-third (22) of the subclusters, attained
190 statistical significance with age ($1.92E-30 \leq FDR \leq 0.046$).

191 The dietary index (the Healthy Eating Index), and an index of health deficit (the
192 frailty index) and antibiotics usage did not produce significant difference in alpha
193 diversity but borderline associations were found with changes in beta diversity
194 (diet, $p = 0.052$, $n = 1004$; recent antibiotics usage, $p = 0.041$, $n = 992$; health deficit,
195 $p = 0.031$, $n = 1139$). Parity trended toward an association with alpha diversity reduction
196 ($p = 0.058$, $n = 1047$), and significantly with beta diversity ($p = 0.026$, $n = 1047$); surgical
197 history did not differ with beta diversity or alpha diversity ($n = 540$). Occurrence of
198 UTI differed with alpha diversity ($p = 0.0027$) and beta diversity ($p = 0.001$). Similar
199 results were obtained using unfrac sample distances or controlling for other factors.

200 The contribution to variance that could be attributed to all factors, including host
201 genetics was then examined (Fig 3). For individuals with virtually all phenotypes
202 ($n = 545$), unique contribution was obtained from R^2 decomposition on microbiome
203 beta diversity estimates, in permutational models (1000 permutations) controlling for
204 other factors. The average for each factor was used after randomly rearranging all

205 factors 20 times. In other scenario of measuring host genetics (Supplementary Data
206 3), but with a smaller sample size, the contribution of host genetics ranks higher.



207
208 **Fig 3. Top contributors to urinary microbiome variation. (A) Relative**
209 **contributions to urinary microbiome.** Bars represents average R^2 for each variable,
210 controlled for the presence of other factors. Microbial variation was measured using
211 Bray-Curtis dissimilarities. Genetic contribution shown was derived from principal
212 components of genetic kinship calculated from whole genome data. **(B-E)**
213 **Microbiome dissimilarities with (B) age (C) menopause (D) prior number of**
214 **UTI. (E) within family of twin pairs (F) Trends in intra-individual Shannon**
215 **diversity with age and prior number of UTI.**

216 Metagenomes confirm overall 16S microbiome data variation

217 Using shotgun metagenome data for a subset of 178 individuals, we also examined
218 how closely the overall patterns of the 16S data are replicated in the metagenome
219 data. The classified metagenome reads were 99.64% Bacteria (Supplementary Data 5)
220 and a greater number of urine metagenomes (total and per individual) were obtained
221 than earlier reported in literature. Sample-sample variation or inter-sample distances
222 in the microbiome data were highly correlated from metagenome and 16S data (for

Atchinson compositions with Euclidean distance, Mantel's $r=0.859$, $p=0.002$; and for Bray dissimilarities, Mantel's $r=0.799$, $p=0.001$). Sixteen of the top 20 abundant taxa are also within the top 20 of the metagenome data. The core microbiome found in 16S data was largely recapitulated in the metagenomics analysis; 27 of the 31 genera (87%) forming the core urobiome using 16S data were also replicated in the metagenome data. From this core, the total number of species identifiable approximately doubled (125 vs 61 in total, 94 vs 53 in the replicated genera) most likely to due to better species assignment.

231

232

233 **Discussion**

In this study, we utilised new approaches in (urinary) microbiome analysis - using amplicon sequence variants rather than OTUs, creating microbial balances from highly frequent taxa, compositional analysis, and eliminating common batch environment effect in twin-pairs - to explore host factors in an relatively large, unselected community-based study population of women. These approaches strengthen deductions made from factors in urinary microbiome variation, for instance, increased diversity with age contrary to previous studies (e.g. Curtiss et al., 2018; Kramer et al., 2018; Liu et al., 2017; Wang et al., 2017).

242 Urine and other body sites

The ordination patterns of the microbiomes support current thinking that the urobiome is a distinct site, similar to the observations that most bladder microbiome (urine obtained directly by catheter) differ from vaginal or stool microbiome (Wolfe & Brubaker, 2019). The more divergent of the urine studies (Urine1 cohort) involved patients with incontinence and collection was wholly catheterized. In a very small minority of individuals where urine microbiome taxa appear closer to stool, this is most likely due to phylogenetic or genome similarity in species (as no such closeness occur with non-phylogenetic measures) rather than common demographics (SFig2). In all, the current study show clear dissimilarities in stool and urine for the average population.

253

254 Host-related factors and host genetics' contribution in urinary microbiome

255 Parity (childbirth episodes), previous UTI occurrence, recent antibiotics usage and
 256 diet showed changes with urine microbiome diversity. Using heritability analysis, the
 257 current study showed a considerable genetic influence in the microbiome of ageing
 258 women, reaching 15% in 57% of urine taxa variation. The remainder of contribution
 259 was largely due to variance unique to individuals. Some clinically important,
 260 “uropathogenic” genera such as *Escherichia* had variants with high heritability
 261 estimates. In addition, *Lactobacillus iners*, a commonly found vaginal microbe which
 262 is phylogenetically close to the heritable gut microbe Christenellaceae was found to
 263 be heritable in urine.

264 Previously, Rothschild and colleagues (2018) reported that environmental factors
 265 such as sharing household may blur genetic influence in gut microbiome composition,
 266 while Goodrich and colleagues (2014) showed host genetics played roles in gut
 267 microbiome patterns of twin-pairs. The current study, indicates significant
 268 contributions of genetics to the pattern of urine microbial composition; and
 269 controlling for cohabitation (participants asked if they live together or close with their
 270 sibling) and other known factors in urine microbial variation, did not alter the
 271 estimated the significant contributions to the pattern. Other parameters from this study
 272 bolster the observation on genetic influence: (1) samples of a member in a twin-pair
 273 were not extracted or sequenced in the same batch as the other member,(2) adding
 274 genetic relatedness statistically explained much more in the pattern of constrained
 275 ordination, (3) there was lower intra-twin difference distance to centroid among
 276 monozygotic pairs, and (4) there were differences along the lines of ethnic ancestry
 277 though the proportion of white British was dominant. Thus we conclude that host
 278 genetics influenced variation in urinary microbiome composition in this population of
 279 women.

280 Relative to other factors, only age, menopause status and prior history of current UTI
 281 were greater than the influence of genetics. Incidental to our main purpose, we also
 282 report here for the first time in humans that history urinary tract infection itself has a
 283 significant heritability as suggested in other species (Norris et al., 2000).

284

285 Heritable urinary pathogens

286 While *Corynebacterium* species were frequent among top core urobiome taxa with
 287 high heritability, the patterns detected for *Lactobacillus iners/jensenii* and
 288 *Escherichia* variants deserve mention. The *Escherichia-Shigella* taxon, renamed as

289 such to reflect the extreme sequence similarity of *Escherichia coli* and *Shigella*, is
 290 apparently ubiquitous in the normal urine microbiota from this data. The current study
 291 shows that presence of this taxon is influenced by (1) host genetic make up (its
 292 proportions had one of the highest heritability estimates ($A=0.17, CI=0.11-0.29$) of all
 293 frequent urine microbial species); and (2) age (its coefficient in age, 0.43, is more
 294 than double that of UTI history, 0.20). The relatively high heritability of these taxa
 295 were also replicated in the subset with metagenomics data and in all, the findings may
 296 have implications in the mixed success of *E. coli* vaccine trials (Huttner et al., 2017).

297

298 The current study has limitations. Questionnaire data, which is subject to accurate
 299 recall and self-report by participants, was part of measures used in deriving variables
 300 such as UTI, diet and frailty. Another limitation may be the use of a single midstream
 301 urine sample set from an individual, and as such, prior microbiome stability
 302 information is unknown. Clearly, further research is needed to confirm if the findings
 303 also relate to the male urinary microbiome.

304

305 To conclude, this is the first ‘large-scale’ human study to identify the factors
 306 influencing composition of the female urinary microbiome. The urinary microbiome
 307 was distinct and apparently unrelated to stool microbiome. It shows a significant
 308 contribution of host genetics. Key species known to have pathogenic potential were
 309 among the most heritable microbes. Age and menopausal status were the factors with
 310 greatest influence on the urinary microbiome in women.

311

312 **Acknowledgement**

313 We thank Dr Alan Wolfe and Roberto Limeira of Health Sciences Division, Loyola
 314 University, Chicago, United States for providing access to raw sequence data from
 315 two urine studies; the phenotype data team at TwinsUK; laboratory team at TwinsUK
 316 for sample handling; and Rachel Horsfall, Marina Mora Ortiz, Mary NiLochlainn for
 317 discussions and comments on the manuscript. CS received research funding through
 318 the Chronic Disease Research Foundation which receives funds from the Denise
 319 Coates Foundation. We also thank all participants in TwinsUK (www.twinsuk.ac.uk).

320

321 **Author Contributions**

322 Conceptualization: C.J.S, T.S. and A.S.A; Investigation: C.J.S., G.H., G.A., R.B.,
 323 P.W. and R.K.; Methodology: C.J.S. and A.S.A.; Formal Analysis: C.J.S. and A.S.A.;
 324 Writing: A.S.A, C.J.S, G.H., T.S. and R.K.; Funding Acquisition: C.J.S. and T.S.;
 325 Supervision: C.J.S., T.S. and R.K.

326

327 **Declaration of Interests**

328 The authors declare no competing interests

329

330

331 **Figure Legends**

332 **Fig 1. Urinary microbiome in older women is mostly distinct from proximal body**
 333 **sites and unrelated to stool microbiome. (A) Alpha diversity of urine**
 334 **microbiomes and other body sites.** star symbol indicates significance compared to
 335 TwinsUK urobiome. **(B) Dissimilarities in urine microbiomes and other body**
 336 **sites.** Plots are based on unifracs distances **(C) Paired alpha diversity analysis of**
 337 **stool and urine collected at same time point (D) Differences in paired stool and**
 338 **urine microbiome from the same time point.**

339

340 **Fig 2. Host genetics considerably influences variation of urine microbiome. (A)**
 341 **Discordance in paired twin types for Euclidean distances to median microbiome**
 342 **in PC.** MZ-monozygotic pair; DZ:Dizygotic pair; PC: principal coordinate **(B).**
 343 **Heritability estimates in species and clusters of highly frequent urinary microbes**
 344 **in paired twins.** Cb represents cluster names, Size of circles at each subcluster and
 345 intensity of rectangular bars at the tips represent increasing heritability of taxa. Taxa
 346 are annotated to indicate different species. Only species in at least 20% of population
 347 form clusters. Clusters are hierarchical but not phylogenetic. **(D). Microbiome**
 348 **principal coordinates with ancestral origin.** White British constitute >90% of
 349 individuals. P-values are derived from permutational models due to imbalanced sizes.
 350 Ellipses represent 95% confidence interval. **(E) Bray dissimilarities with the ethnic**
 351 **or ancestry divisions.**

352

353 **Fig 3. Top contributors to urinary microbiome variation. (A) Relative**
 354 **contributions to urinary microbiome.** Bars represents average R^2 for each variable,
 355 controlled for the presence of other factors. Microbial variation was measured using

Bray-Curtis dissimilarities. Genetic contribution shown was derived from principal components of genetic kinship calculated from whole genome data. **(B-E) Microbiome dissimilarities with (B) age (C) menopause (D) prior number of UTI. (E) within family of twin pairs (F) Trends in intra-individual Shannon diversity with age and prior number of UTI.**

Tables

Table 1. Summary of participants in TwinsUK urinary microbiome study

Phenotype category	Subcategory	α -D index (mean \pm SD)	Ave. no of unique taxa(mean \pm SD)	No. of samples	Age (mean \pm SD)
Participants		2.01 \pm 1.05	65.7 \pm 48.8	1600	66.7 \pm 8.3
Previous UTI occurrence ^s	0 times	2.14 \pm 1.0	66.1 \pm 43.1	393	67.6 \pm 8.2 ^s
	1-4 times	2.02 \pm 1.04	67.5 \pm 51.0	719	65.9 \pm 7.8
	5-9 times	1.98 \pm 1.03	65.4 \pm 45.2	208	66.3 \pm 8.3
	10times >	1.79 \pm 1.17	60.0 \pm 53.9	201	65.7 \pm 8.3
Age ^s	<50-54	1.56 \pm 0.76	45.9 \pm 32.2	117	-
	55-59	1.86 \pm 1.13	61.7 \pm 49.7	210	-
	60-64	2.00 \pm 0.98	63.5 \pm 44.8	327	-
	65-69	2.04 \pm 1.03	66.0 \pm 49.8	409	-
	70-74	2.16 \pm 0.97	71.5 \pm 50.6	276	-
	75-79	2.26 \pm 1.12	74.5 \pm 50.1	170	-
	80-84	2.02 \pm 1.12	63.7 \pm 41.9	68	-
	85-	1.73 \pm 1.42	71.7 \pm 62.3	23	-
RecentAntibiotic usage:3mths	Yes	1.97 \pm 1.20 ^{ns}	70.0 \pm 53.0 ^{ns}	47	68.3 \pm 8.0 ^{ns}
	No	2.03 \pm 1.06	66.0 \pm 49.0	945	66.6 \pm 8.3
Frailty	<0.15	2.05 \pm 1.01 ^{ns}	67.0 \pm 49.0 ^{ns}	511	65.9 \pm 7.5 ^s
	0.15-0.29	1.99 \pm 1.05	64.8 \pm 49.0	834	66.1 \pm 8.0
	0.3-0.44	2.04 \pm 1.15	67.5 \pm 48.0	227	68.4 \pm 8.9
	>0.45	1.75 \pm 1.17	62.0 \pm 47.0	28	68.5 \pm 8.2

Legend. α -D: Shannon H index of alpha diversity; No. of taxa refers to number of unique sequence variant per sample i.e. no of potential species. Diversity measures were calculated after subsampling to 2000. S/NS indicates statistical significance or not for tests of a phenotype as a continuous variable. Post-hoc pairwise comparisons showed no difference in alpha diversity after 75years.

STAR Methods

2.1 Cohort and Phenotypes

377 The TwinsUK cohort has been described elsewhere (Verdi et al. 2019). Participants in
378 the cohort are community dwelling twin pairs, recruited without any specific clinical
379 phenotype. Various demographics were examined. Medical history questionnaires
380 were used to define age (from birth date), history of urinary tract infections (UTIs),
381 cohabitation, antibiotic usage, previous hysterectomy, previous oophorectomy,
382 caesarian section and menopause status. The frailty index, calculated from clinical,
383 physiological and mental domains (Livshits et al., 2017) was used as a measure of
384 health deficit, and the Healthy Eating Index (Bowyer et al. 2018) based on food
385 frequency questionnaires used to assess diet.

386 2.2 16S Microbiome Sequencing and Analysis

387 Twin-pair samples were separated for processing. Extraction and Sequencing was
388 performed at the Knight Lab, University of California San Diego. A low biomass
389 pipeline designed to extract optimal yields of DNA was used with 16S V4 marker-
390 based paired-end sequencing on IlluminaMiSeq platform. Multilevel quality filtering
391 procedures and data analysis were applied to remove potential contaminants (Suppl
392 Methods). In summary, amplicon sequence variants (ASVs), were filtered, and
393 analysed as individual taxa and as clusters based on highly frequent variants, with
394 subsequent compositional balance transformations (Morton et al., 2017)
395 (Supplementary Methods). The current data was also compared to those of previous
396 microbiome studies with similar age-range of participants after re-analysis of such
397 data to produce ASVs (Supplementary Methods). Diversity analysis was carried out
398 with Shannon index, Unifrac, Bray and Atchinson distances, and permutational
399 analysis of variance was used to test inter-sample differences. Taxa counts were
400 centred-log ratio transformed after adding a pseudocount of 1, and independent taxa
401 associations were pruned for presence in at least 5% of samples.

403 2.3 Metagenome Analysis

404 Shotgun metagenomic sequencing was carried out for 178 of the participants using
405 newer approaches (Hillman et al., 2018), with additional 14 blanks for quality control.
406 This subset of participants were chosen to include equal numbers of dizygotic pairs
407 and monozygotic twin pairs, as well as equal numbers of twin pairs showing
408 discordance and concordance in 16S microbial diversity. After quality control
409 filtering, and mapped human reads removal (based on hg19) one sample was

410 excluded, and the final analysis included 177 samples, comprising 43 pairs of
411 dizygotic twins and 45 pairs of monozygotic twins (n=176). Potential contaminant
412 species were also removed (Supplementary Methods).

413

414 2.4 Host genetics analyses

415 Heritability was calculated using an ACE model in which the component of
416 phenotypes explained by genetics in twin pairs was estimated. Samples from co-twin
417 were separated into different batches for sample preparation and sequencing to
418 remove the shared technical environment related to batching. This further solidified
419 the deductions made from the analysis of the genetic effects. Where constrained
420 principal coordinates analysis was used, microbiome data was ordinated with the
421 family ID tested as a predictor, then the dissimilarity within a family was then
422 extracted to compare twin types. Discordance analysis was based on quantitative
423 difference in pairs of monozygotic and dizygotic twins. Analysis on ethnic origin of
424 participants based on information obtained from questionnaires. To represent host
425 genetic variation, first principal component from SNP-based kinship data, raw whole
426 genomic sequence data (available for a separate subset of unrelated participants)
427 which were part of a previous study (Long et al. 2017), and zygosity:family nested
428 model variance (only for twin-pairs) were obtained. Each of these were analysed
429 separately as a measure of genetic relatedness.

430

431 Throughout analysis, technical covariates, including extraction kit lots, mastermix kit
432 lot, batch, extraction and sequencing processors, and depth/library sizes (sequence
433 reads post-QC filtering) were controlled for. Raw sequence data is available from
434 qiita, phenotype data is available on request TwinsUK data access committee at
435 <http://twinsuk.ac.uk/resources-for-researchers/access-our-data.html>. Scripts and
436 codes used are available at github.com/urobiome-host-genetics

437

438 **Supplemental Information**

439

440 **SFig1A-B. Replicate diversity analysis to compare urinary microbiome from**
441 **various body sites. (C). Plots showing the ordination of paired stool and urine**

442 **samples (D) Top heritable species.** Species displayed in line bars have more than
 443 15% heritability and star symbol indicate species detected in at least 20%.
 444 **(E). Phylogenetic tree of frequent species in urinary microbiome of older women**
 445 **and their heritability.** Tree edges and branch length are coloured by increasing
 446 heritability estimates (from green to red). Species displayed in tree were detected at
 447 least 5% of study population.

448
 449 **SFig2. Comparison of demographics for individuals with closer urine and gut**
 450 **microbiome**

451 **SFig3. Comparison of top abundant urinary microbiome taxa using various**
 452 **approaches**

453 **SFig4 Additional variation explained from relatedness in twin pairs. A without**
 454 **relatedness B. with relatedness**

455 456 **References**

- 457 Adebayo, A.S., Survayanshi, M., Bhute, S., Agunloye, A.M., Isokpehi, R.D., Anumudu, C.I., and
 458 Shouche, Y.S. (2017). The microbiome in urogenital schistosomiasis and induced bladder pathologies.
 459 PLoS Negl. Trop. Dis. *11*.
 460 Alanee, S., El-Zawahry, A., Dynda, D., McVary, K., Karr, M., and Braundmeier-Fleming, A. (2019).
 461 Prospective examination of the changes in the urinary microbiome induced by transrectal biopsy of the
 462 prostate using 16S rRNA gene analysis. Prostate Cancer Prostatic Dis.
 463 Aragón, I.M., Herrera-Imbroda, B., Queipo-Ortuño, M.I., Castillo, E., Del Moral, J.S.G., Gómez-
 464 Millán, J., Yucel, G., and Lara, M.F. (2018). The Urinary Tract Microbiome in Health and Disease.
 465 Eur. Urol. Focus *4*, 128–138.
 466 Bowyer, R.C.E., Jackson, M.A., Pallister, T., Skinner, J., Spector, T.D., Welch, A.A., and Steves, C.J.
 467 (2018). Use of dietary indices to control for diet in human gut microbiota studies. Microbiome *6*, 77
 468 Brown, K., Church, D., Lynch, T., and Gregson, D. (2014). Bloodstream infections due to
 469 Peptoniphilus spp.: Report of 15 cases. Clin. Microbiol. Infect. *20*, O857–O860.
 470 Curtiss, N., Balachandran, A., Krska, L., Peppiatt-Wildman, C., Wildman, S., and Duckett, J. (2018).
 471 Age, menopausal status and the bladder microbiome. Eur. J. Obstet. Gynecol. Reprod. Biol. *228*, 126–
 472 129.
 473 Eline Slagboom, P., van den Berg, N., and Deelen, J. (2018). Phenome and genome based studies into
 474 human ageing and longevity: An overview. Biochim. Biophys. Acta - Mol. Basis Dis. *1864*, 2742–
 475 2751.
 476 Felice, V.D., and O'Mahony, S.M. (2017). The microbiome and disorders of the central nervous
 477 system. Pharmacol. Biochem. Behav. *160*, 1–13.
 478 Fok, C.S., Gao, X., Lin, H., Thomas-White, K.J., Mueller, E.R., Wolfe, A.J., Dong, Q., and Brubaker,
 479 L. (2018). Urinary symptoms are associated with certain urinary microbes in urogynecologic surgical
 480 patients. Int. Urogynecol. J. *29*, 1765–1771.
 481 Franco, A.V. (2005). Recurrent urinary tract infections. Best Practice & Research Clinical Obstetrics
 482 and Gynaecology. *19*, 861–873.
 483 Goodman, B., and Gardner, H. (2018). The microbiome and cancer. J. Pathol. *244*, 667–676.
 484 Goodrich, J.K., Waters, J.L., Poole, A.C., Sutter, J.L., Koren, O., Blekhman, R., Beaumont, M., Van

485 Treuren, W., Knight, R., Bell, J.T., et al. (2014). Human genetics shape the gut microbiome. *Cell* 159,
486 789–799.

487 Karstens, L., Asquith, M., Caruso, V., Rosenbaum, J.T., Fair, D.A., Braun, J., Gregory, W.T., Nardos,
488 R., and McWeeney, S.K. (2018). Community profiling of the urinary microbiota: considerations for
489 low-biomass samples. *Nat. Rev. Urol.* 15, 735–749.

490 Kline, K.A., and Lewis, A.L. (2016). Gram-Positive Uropathogens, Polymicrobial Urinary Tract
491 Infection, and the Emerging Microbiota of the Urinary Tract. *Microbiol. Spectr.* 4.

492 Könönen, E., and Wade, W.G. (2015). Actinomyces and related organisms in human infections. *Clin.*
493 *Microbiol. Rev.* 28, 419–442.

494 Kramer, H., Kuffel, G., Thomas-White, K., Wolfe, A.J., Vellanki, K., Leehey, D.J., Bansal, V.K.,
495 Brubaker, L., Flanigan, R., Koval, J., et al. (2018). Diversity of the midstream urine microbiome in
496 adults with chronic kidney disease. *Int. Urol. Nephrol.* 50, 1123–1130.

497 Livshits, G., Lochlainn, M.N., Malkin, I., Bowyer, R., Verdi, S., Steves, C.J., and Williams, F.M.K.
498 (2018). Shared genetic influence on frailty and chronic widespread pain: A study from TwinsUK. *Age*
499 *Ageing* 47, 119–125.

500 Luca F., Kupfer S.S., Knights D, Khoruts A and Blekhman R. (2018). Functional Genomics of Host–
501 Microbiome Interactions in Humans. *Trends in Genetics* 34,30–40.

502 Ma, Z. (Sam), Li, L., and Gotelli, N.J. (2019). Diversity-disease relationships and shared species
503 analyses for human microbiome-associated diseases. *ISME J.* 1.

504 Moayyeri, A., Hammond, C.J., Hart, D.J., and Spector, T.D. (2013). The UK adult twin registry
505 (twinsUK resource). *Twin Res. Hum. Genet.* 16, 144–149.

506 Morton, J.T., Sanders, J., Quinn, R.A., McDonald, D., Gonzalez, A., Vázquez-Baeza, Y., Navas-
507 Molina, J.A., Song, S.J., Metcalf, J.L., Hyde, E.R., et al. (2017). Balance Trees Reveal Microbial Niche
508 Differentiation. *MSystems* 2, 1–11.

509 Moustafa, A., Li, W., Singh, H., Moncera, K.J., Torralba, M.G., Yu, Y., Manuel, O., Biggs, W.,
510 Venter, J.C., Nelson, K.E., et al. (2018). Microbial metagenome of urinary tract infection. *Sci. Rep.* 8,
511 1–12.

512 Pearce, M.M., Hilt, E.E., Rosenfeld, A.B., Zilliox, M.J., Thomas-White, K., Fok, C., Kliethermes, S.,
513 Schreckenberger, P.C., Brubaker, L., Gai, X., et al. (2014). The female urinary microbiome: A
514 comparison of women with and without urgency urinary incontinence. *MBio* 5.

515 Rothschild, D., Weissbrod, O., Barkan, E., Kurilshikov, A., Korem, T., Zeevi, D., Costea, P.I.,
516 Godneva, A., Kalka, I.N., Bar, N., et al. (2018). Environment dominates over host genetics in shaping
517 human gut microbiota. *Nature* 555, 210–215.

518 Shrestha, E., White, J.R., Yu, S.H., Kulac, I., Ertunc, O., De Marzo, A.M., Yegnasubramanian, S.,
519 Mangold, L.A., Partin, A.W., and Sfanos, K.S. (2018). Profiling the Urinary Microbiome in Men with
520 Positive versus Negative Biopsies for Prostate Cancer. *J. Urol.* 199, 161–171.

521 Sihra, N., Goodman, A., Zakri, R., Sahai, A., and Malde, S. (2018). Nonantibiotic prevention and
522 management of recurrent urinary tract infection. *Nat. Rev. Urol.* 15, 750–776.

523 Thomas-White, K.J., Hilt, E.E., Fok, C., Pearce, M.M., Mueller, E.R., Kliethermes, S., Jacobs, K.,
524 Zilliox, M.J., Brincat, C., Price, T.K., et al. (2016). Incontinence medication response relates to the
525 female urinary microbiota. *Int. Urogynecol. J.* 27, 723–733.

526 Thomas-White, K.J., Kliethermes, S., Rickey, L., Lukacz, E.S., Richter, H.E., Moalli, P., Zimmern, P.,
527 Norton, P., Kusek, J.W., Wolfe, A.J., et al. (2017). Evaluation of the urinary microbiota of women with
528 uncomplicated stress urinary incontinence. *Am. J. Obstet. Gynecol.* 216, 55.e1–55.e16.

529 Verma, R., Morrad, S., and Wirtz, J.J. (2017). *Peptoniphilus asaccharolyticus* -associated septic
530 arthritis and osteomyelitis in a woman with osteoarthritis and diabetes mellitus. *BMJ Case Rep.* 2017.

531 Whiteside, S.A., Razvi, H., Dave, S., Reid, G., and Burton, J.P. (2015). The microbiome of the urinary
532 tract - A role beyond infection. *Nat. Rev. Urol.* 12, 81–90.

533 Wolfe, A.J., and Brubaker, L. (2019). Urobiome updates: advances in urinary microbiome research.
534 *Nat. Rev. Urol.* 16, 73–74.

535 Wolfe, A.J., Toh, E., Shibata, N., Rong, R., Kenton, K., FitzGerald, M.P., Mueller, E.R.,
536 Schreckenberger, P., Dong, Q., Nelson, D.E., et al. (2012). Evidence of uncultivated bacteria in the

537 adult female bladder. *J. Clin. Microbiol.* 50, 1376–1383.

538 Wu, P., Chen, Y., Zhao, J., Zhang, G., Chen, J., Wang, J., and Zhang, H. (2017). Urinary microbiome
539 and psychological factors in women with Overactive bladder. *Front. Cell. Infect. Microbiol.* 7.

540

541 El-Zawahry, A., Dynda, D., McVary, K., Karr, M., and Braundmeier-Fleming, A. (2019). Prospective
542 examination of the changes in the urinary microbiome induced by transrectal biopsy of the prostate
543 using 16S rRNA gene analysis. *Prostate Cancer Prostatic Dis.*

544

545 Hillmann, B., Al-ghalith, G.A., Shields-cutler, R.R., Zhu, Q., Gohl, D.M., Beckman, K.B., Knight, R.,
546 and Knights, D. (2018). crosssm Metagenomics. *MSystems* 3, 1–12.

547 Huttner, A. et al. (2017). Safety, immunogenicity, and preliminary clinical efficacy of a vaccine against
548 extraintestinal pathogenic *Escherichia coli* in women with a history of recurrent urinary tract infection:
549 a randomised, single-blind, placebo-controlled phase 1b trial. *Lancet Infect. Dis.* 17, 528–537.

550

551 Liu, F., Ling, Z., Xiao, Y., Yang, Q., Zheng, L., Jiang, P., Li, L., and Wang, W. (2017).
552 Characterization of the urinary microbiota of elderly women and the effects of type 2 diabetes and
553 urinary tract infections on the microbiota. *Oncotarget* 8, 100678–100690.

554

555 Rani, A., Ranjan, R., McGee, H.S., Andropolis, K.E., Panchal, D. V., Hajjiri, Z., Brennan, D.C., Finn,
556 P.W., and Perkins, D.L. (2017). Urinary microbiome of kidney transplant patients reveals dysbiosis
557 with potential for antibiotic resistance. *Transl. Res.* 181, 59–70.

558

559 Verdi, Serena, Golboo Abbasian, Ruth C. E Bowyer, Genevieve Lachance, Darioush Yarand,
560 Paraskevi Christofidou, Massimo Mangino, Cristina Menni, Jordana T. Bell, Mario Falchi, Kerrin S.
561 Small, Frances M. K Williams, Christopher J. Hammond, Deborah J. Hart, C.J.S. (2019). TwinsUK:
562 The UK Adult Twin Registry. *Twin Res. Hum. Genet.* *Accepted*.

563

564 Wang, H., Altemus, J., Niazi, F., Green, H., Calhoun, B.C., Sturgis, C., Grobmyer, S.R., and Eng, C.
565 (2017). Breast tissue, oral and urinary microbiomes in breast cancer. *Oncotarget* 8, 88122–88138.

566

567