

1 **Title:** Age and sex-dependent patterns of gut microbial diversity in human adults

2

3 **Authors/Address/Email:**

4

5 Jacobo de la Cuesta-Zuluaga¹

6 Department of Microbiome Science, Max Planck Institute for Developmental Biology, 72076

7 Tübingen, Germany.

8 Email: jacobo.delacuesta@tuebingen.mpg.de

9

10 Scott T. Kelley¹

11 Department of Biology, San Diego State University, San Diego, California, USA

12 Email: skelley@sdsu.edu

13

14 Yingfeng Chen

15 Department of Biology, San Diego State University, San Diego, California, USA

16 Email: cyf298@hotmail.com

17

18 Juan S. Escobar

19 Vidarium-Nutrition, Health and Wellness Research Center, Grupo Empresarial Nutresa,

20 Medellin, Colombia

21 Email: jsescobar@serviciosnutresa.com

22

23 Noel T. Mueller

24 Department of Epidemiology, Johns Hopkins Bloomberg School of Public Health, Baltimore,

25 MD, USA

26 Welch Center for Epidemiology, Prevention and Clinical Research, Johns Hopkins Medical

27 Institutions, Baltimore, MD, USA

28 Email: noelmueller@jhu.edu

29

30 Ruth E. Ley

31 Department of Microbiome Science, Max Planck Institute for Developmental Biology, 72076

32 Tübingen, Germany.

33 Email: ruth.ley@tuebingen.mpg.de

34

35 Daniel McDonald

36 Department of Pediatrics, University of California San Diego, La Jolla, California, USA

37 Email: danielmcdonald@ucsd.edu

38

39 Shi Huang

40 Department of Pediatrics, University of California San Diego, La Jolla, California, USA

41 Email: shh047@ucsd.edu

42

43 Austin D. Swafford

44 Center for Microbiome Innovation, University of California, La Jolla, California, USA

45 Email: adswafford@ucsd.edu

46

47 Rob Knight

48 Department of Pediatrics, University of California San Diego, La Jolla, California, USA

49 Department of Computer Science, University of California San Diego, La Jolla, California, USA

50 Department of Bioengineering, University of California San Diego, La Jolla, California, USA

51 Center for Microbiome Innovation, University of California, La Jolla, California, USA

52 Email: robknight@ucsd.edu

53

54 Varykina G. Thackray*

55 Department of Obstetrics, Gynecology and Reproductive Sciences, University of California San

56 Diego, La Jolla, California, USA

57 Email: vthackray@ucsd.edu

58

59 ¹Contributed equally to this work

60 *Corresponding Author

61

62 Keywords: Diversity, Sex, Age, Microbiome; 16S rRNA amplicon

63

64

65 **Abstract**

66

67 Gut microbial diversity changes throughout the human lifespan and is known to be affected by
68 host sex. We investigated the association of age, sex and gut bacterial alpha diversity in three
69 large cohorts of adults from four geographical regions: US and UK cohorts in the American Gut
70 Project, and two independent cohorts of Colombians and Chinese. In three of the four cohorts,
71 we observed a strong positive association between age and alpha diversity in young adults that
72 plateaued after age 40. We also found pronounced sex-dependent differences in younger but
73 not middle-aged adults, and women had higher alpha diversity than men. In contrast, no
74 association of alpha diversity with age or sex was observed in the Chinese cohort. These
75 associations were maintained after adjusting for cardiometabolic parameters in the Colombian
76 cohort and antibiotic usage in the AGP cohort, suggesting that these factors do not affect the
77 association of alpha diversity with age and sex. We also used a machine learning approach to
78 predict individual age based on the gut microbiome. Consistent with our alpha diversity-based
79 findings, women had significantly higher predicted age than men in the US and UK cohort, with
80 a reduced difference above age 40. This was not observed in the Colombian cohort and only in
81 the group of middle-age adults in the Chinese cohort. Together, our results provide new insights
82 into the influence of age and sex on biodiversity of the human gut microbiota during adulthood
83 while highlighting similarities and differences across diverse cohorts.

84

85 **Importance**

86

87 Bacteria in the human gut play important roles in health and disease, and higher gut biodiversity
88 has been linked to better health. Since gut bacteria may be pivotal in the development of
89 microbial therapies, understanding the factors that shape gut biodiversity is of utmost interest.
90 We performed large-scale analyses of the relationship of age and sex to gut bacterial diversity
91 in adult cohorts from four geographic regions: US, UK, Colombia and China. In the US, UK and
92 Colombia cohorts, bacterial biodiversity correlated positively with age in young adults, but
93 plateaued around age 40 with no positive correlation in middle-aged adults. Young, but not
94 middle-aged, adult women had higher gut bacterial diversity than men, a pattern confirmed via
95 deep machine-learning. Interestingly, in the Chinese cohort, minimal associations were
96 observed between gut biodiversity and age or sex. Our results highlight patterns of adult gut
97 biodiversity and provide a framework for future research.

98

99

100 **Introduction**

101 The human gut microbiota is a highly diverse ecosystem that is extremely variable amongst
102 individuals (Lloyd-Price et al., 2017). This microbial community has been shown to play a key
103 role in human health and disease (Gilbert et al., 2016). Since the gut microbiota may be pivotal
104 to the development of microbial therapies, understanding factors that shape overall gut
105 microbiota biodiversity over the different human life stages is of utmost interest.

106 There is increasing evidence suggesting that the host genes, gene expression patterns,
107 environmental exposures, including medication and diet, and lifestyle factors play an important
108 role in delimiting the boundaries of microbial diversity in the gut (Foster et al., 2017; McDonald
109 et al., 2018). While a detailed longitudinal study of the interplay of each of these factors would
110 be scientifically, logistically, and financially challenging, the chronological age of the host may
111 be conceived as a proxy variable that represents the accumulation of these effects for a given
112 individual. Several studies have reported a positive correlation between age and gut microbiota
113 alpha diversity from birth to adulthood (Hopkins et al., 2002; Koenig et al., 2011; Mariat et al.,
114 2009; Yatsunenکو et al., 2012). Likewise, it has been shown that alpha diversity is maintained in
115 old age until comorbidities contribute to its decline (Maffei et al., 2017). Another intriguing host-
116 associated pattern identified in humans and rodents is the link between the gut microbiota and
117 sex. Recent studies reported that women have higher microbial diversity than men and that sex
118 influences the composition of the microbial community after puberty (Falony et al., 2016; Kozik
119 et al., 2017; Markle et al., 2013; Sinha et al., 2018; Yatsunenکو et al., 2012). These differences
120 may contribute to the sexual dimorphism of autoimmune (Gomez et al., 2012; Markle et al.,
121 2013; Yurkovetskiy et al., 2013) and neuro-immune diseases (Wallis et al., 2017, 2016).
122 Therefore, it is key to consider the impact of inherent age and sex differences in different human
123 populations to adequately discriminate changes and variations in the microbiome of individuals.

124 To better understand how age and sex of the host relate to the diversity of the gut
125 microbiota during adulthood, we explored the association of these factors using data from
126 individuals in three cross-sectional studies from four geographical origins including the citizen-
127 science American Gut Project (AGP) comprised of individuals from the United States (US) and
128 the United Kingdom (UK) (McDonald et al., 2018), a cohort of individuals from China (He et al.,
129 2018) and a relatively smaller study with individuals from Colombia (de la Cuesta-Zuluaga et al.,
130 2018).

131 **Materials and Methods**

132 *Cohort description*

133
134
135 Fecal samples were obtained from individuals in three independent cohorts from four
136 geographical locations: i) The AGP dataset is composed of two cohorts with individuals from the
137 UK (539 women and 397 men), and the US (1361 women and 1227 men) (Table 1); healthy
138 participants self-reported age between 20 and 69, a body mass index (BMI) between 18.5 and
139 30 kg/m², and no history of inflammatory bowel disease, diabetes, or antibiotic use in the past
140 year. ii) A cohort of Chinese individuals (2772 women and 2191 men) aged 20 to 69, with BMI
141 ranging from 18.5 to 30 kg/m² and no antibiotic consumption reported one month prior to fecal
142 sample collection; pregnant women, and hospitalized, disabled or critically-ill individuals were
143

144 not included in the study. iii) A cohort of community-dwelling Colombians (226 women and 211
145 men), 20 to 62 years of age, enrolled in similar proportions according to: BMI, city of residence,
146 and age range (20-40 and 41-62 years); underweight participants, pregnant women, individuals
147 who had consumed antibiotics or antiparasitics in the three months prior to enrollment, and
148 individuals diagnosed with neurodegenerative diseases, current or recent cancer (<1 year), and
149 gastrointestinal diseases were excluded. Details on the data acquisition, quality assessment
150 and processing of fecal samples from these three cohorts were previously described (de la
151 Cuesta-Zuluaga et al., 2018; He et al., 2018; McDonald et al., 2018).

152

153 *16S rRNA gene sequence processing*

154

155 Amplicon sequences of all three cohorts were uniformly processed following the same
156 procedures previously described (McDonald et al., 2018). Briefly, the V4 hypervariable region of
157 the 16S rRNA gene was sequenced with the Illumina MiSeq platform. Raw sequences were
158 clustered into sequence variants (SV) with deblur denoising (Amir et al., 2017) using QIIME 2
159 (Bolyen et al., 2018). Sequence counts were rarefied to 1250 reads per sample across all
160 samples to mitigate uneven sequencing depth. Note, however, that sample collecting and DNA
161 extraction methods differed between studies.

162

163 *Statistical analyses*

164

165 SV richness and Shannon index were calculated using QIIME 2 and statistical analyses were
166 performed using R v.3.4.3. The association of age and alpha diversity was measured with and
167 without separate age groups by fitting linear models with linear splines with a knot at age 45
168 (lspline v.1.0 package of R) or simple linear models, respectively. We assessed the goodness of
169 fit of these models by means of the Akaike's information criterion (AIC). Next, scatter plots of
170 each alpha diversity metric according to age were constructed and then separate LOESS
171 curves for women and men were fitted using the ggplot2 v.3.0 package of R. Given the
172 nonlinear association observed between alpha diversity and age, we subdivided the datasets
173 into two separate age groups: 20 to 45 years (young adult) and 46 to 69 years (middle-aged
174 adult), which were then used to fit linear models to test associations of age (as a continuous
175 variable) and alpha diversity measures, stratified by sex.

176

177 Additionally, to account for possible confounder effects of antibiotic usage or
178 cardiometabolic health of the subjects, we replicated the above analyses as follows. For the
179 former, we replicated the analyses using a separate group of individuals of the AGP cohort from
180 the US who had consumed antibiotics during the 6 months prior to their enrollment (283 women
181 and 174 men). For the latter, we replicated the analyses adjusting the linear models for
182 cardiometabolic risk in the Colombian cohort using a risk measure, which we termed
183 cardiometabolic risk scale (Guzman-Castaneda et al., 2018). This was calculated using the sum
184 of the z-scores of log-transformed waist circumference, triglycerides, insulin, diastolic blood
185 pressure and high-sensitivity C reactive protein; positive values of the score are associated with
186 increased cardiometabolic health risk.

186

187 Random Forest (RF) regression was used to regress relative abundances of SVs in the
188 gut microbiota of healthy women and men adults against their chronological age in each

188 dataset, using the R package randomForest and the following parameters: ntree = 18,000 and
189 mtry = $p/3$, where p is the number of input features (SVs). The microbiota age model was first
190 trained on the training dataset of female adults and was then applied to test the set of male
191 adults, and vice versa. A smoothing spline function was fit between microbiota age and
192 chronological age of the hosts for calculation of “relative microbiota age” of adults in the test
193 sets to which the sparse model was applied. For a particular sample, the relative microbiota age
194 was calculated as the difference between the “microbiota age of a focal adult” and the
195 “microbiota age of interpolated spline fit of healthy women/men adults at the same chronological
196 age”. We further employed Wilcoxon rank-sum test to compare the relative microbiota age
197 between female and male groups in each of datasets using the R function Wilcox.test. To
198 establish the sex difference in microbiota age, we subdivided the datasets into the above-
199 defined age groups, and repeated the analyzes as described above in all age segments.

200 The code and data required to reproduce the statistical analyses is available at
201 https://github.com/jacodela/microbio_aDiv.

202

203 Results

204

205 Basic characteristics of individuals from the four cohorts are summarized in Table 1,
206 stratified by sex and age group. To assess changes in alpha diversity with age during
207 adulthood, we first performed linear regression with linear splines, establishing a knot at 45
208 years of age, and simple linear regressions in each cohort independently. We then evaluated
209 the goodness of fit of each model using AIC, which indicated that changes in alpha diversity are
210 better explained by distinguishing between young adults (20-45 years) and middle-aged adults
211 (46-69 years). In the US, UK and Colombian cohorts, we observed a positive but non-linear
212 association between alpha diversity measures and age, in both women and men. LOESS
213 curves fit independently by sex showed an inflection point after age 40 in each of these cohorts
214 (Fig. 1A-C). In contrast, we did not observe such a pattern in the Chinese cohort, in which alpha
215 diversity displayed a slight decrease with age (Fig. 1D).

216 We then fit linear regression models to examine associations of microbial diversity, age
217 and sex in the different age groups of each cohort independently. In both the US and UK
218 cohorts, we observed a positive relationship between microbial richness and age for both sexes
219 in young adults (US: $p < 0.001$; UK: $p < 0.001$), but not in middle-aged adults (US: $p = 0.404$;
220 UK: $p = 0.111$) (Fig. 1A-B). In addition, after adjusting for age we observed significant or
221 borderline significant differences in overall SV richness between sexes in young adults (US:

222 $\Delta_{\text{men} - \text{women}} = -3.3.$, $p\text{-value} = 0.066$; UK: $\Delta_{\text{men} - \text{women}} = -9.84$, $p\text{-value} = 0.003$) but not middle-aged

223 adults (US: $\Delta_{\text{men} - \text{women}} = -1.3$, $p\text{-value} = 0.48$; UK: $\Delta_{\text{men} - \text{women}} = -3.7$, $p\text{-value} = 0.24$). Similar

224 results were observed when we assessed taxa evenness using the Shannon index (Fig. S1).

225 Finally, we observed a significant interaction between age and sex with the Shannon index, but
226 not SV richness, in young (Shannon US: $p = 0.02$; Shannon UK: $p = 0.03$; SV richness US: $p =$
227 0.15 ; SV richness UK: $p = 0.09$) but not middle-aged adults ($p > 0.2$ all comparisons).

228 To establish whether these trends were present in other populations, we then examined
229 the association of alpha diversity with age and sex in the different age groups of cohorts from
230 Colombia and China. Similar to the US and UK cohorts from the AGP, we identified a positive

231 relationship between richness and age in the Colombian cohort in young adults of both sexes
232 (p-value = 0.002) but not in middle-aged adults (p-value = 0.722) (Fig. 1C). Likewise, there was
233 a significant difference in overall SV richness between the sexes in young adults ($\Delta_{\text{men} - \text{women}} = -$
234 10.0; p-value = 0.006) but not in middle-aged adults ($\Delta_{\text{men} - \text{women}} = -7.3$; p-value = 0.15).
235 Potentially due to a smaller sample size, we did not find a significant interaction between age
236 and sex on microbial diversity in the Colombian cohort for young (p = 0.91) or middle-aged
237 adults (p = 0.81). In contrast to the US, UK and Colombian cohorts, we did not observe a
238 relationship between biodiversity and age in young adults from the Chinese cohort (Fig. 1D).
239 Men in the Chinese cohort tended to have lower SV richness compared to women as young
240 adults, yet the difference was not significant (young adults: $\Delta_{\text{men} - \text{women}} = -4.46$, p-value = 0.051;
241 middle-aged adults: $\Delta_{\text{men} - \text{women}} = -4.08$, p-value = 0.63).

242 Given that gut microbial diversity may be affected by factors such as antibiotic use or the
243 cardiometabolic health of the host, we replicated the above analyses in cohorts in which we
244 observed the patterns making use of publicly available metadata. To test whether the
245 consumption of antibiotics affected the observed pattern, we performed the above analyses on
246 a set of 457 individuals (283 women and 174 men) from the US cohort of the AGP that reported
247 having consumed antibiotics in the 6 months prior to enrollment. As expected, we observed
248 lower SV richness in these individuals compared to those that did not consume antibiotics.
249 Additionally, our results indicated that the usage of antibiotics did not degrade the association of
250 alpha diversity with age or sex in the AGP cohort (Fig. 2). Likewise, we replicated the analyses
251 in the Colombian cohort after introducing a composite measure of the cardiometabolic health of
252 the subjects as a covariate to the linear models; after we adjusted analyses for cardiometabolic
253 health score, the observed patterns were similar (Fig. 3).

254 To examine whether similar age and sex-associated patterns in the gut microbiota would
255 be observed applying an orthogonal method, we utilized a supervised machine learning
256 approach using the composition of the gut microbiota of the subjects of the different populations.
257 We subdivided each cohort by sex, determined the SVs shared by both groups, and used their
258 relative abundances and the chronological age at time of sample collection of the host to fit a
259 random forest (RF) regression model. Two models were built for women and men groups aged
260 from 20-69 years; each trained using one sex and tested on the other. For each subject, we
261 calculated the relative microbiota age as the difference between its microbiota age and the
262 microbiota age of interpolated spline fit of an individual of the opposite sex at the same
263 chronological age. Overall, our results indicate that the regressions can explain only 7-10 % of
264 the variance in chronological age (from 20-69 years) of unrelated healthy adults from the US
265 cohort.

266 We used 1494 shared SVs between women and men to build the RF model of the US
267 cohort (Fig. 4A). We found that men exhibited lower relative microbiota age than women
268 (p=6.237e-14, Wilcoxon rank-sum test; Fig. 4B, upper panels), suggesting sex may affect the
269 adult gut microbial aging process. To validate this finding, we also trained a RF model in the
270 men group and then applied to women (Fig. 4A, lower panels); we found women had higher
271 microbiota age (p=2.467e-12, Wilcoxon rank-sum test. Fig. 4B, lower panels). To establish
272 whether these trends were present in different age groups, we then examined the sex-

273 dependent association of microbiota age in young and middle-aged separately. In the young
274 group, we selected the 1311 shared SVs between both sexes to build the RF model for women
275 and then applied it to predict the microbiota age of men. Compared to men, we found young
276 women exhibited slightly higher relative microbiota age ($p=0.0003225$. Fig. 4C, D, upper
277 panels). Similar results were observed when we assessed microbiota age in the middle-aged
278 group, in which we used the 1601 shared SVs sexes to build the RF model as above. Microbiota
279 age was higher in women compared to men ($p=3.895e-15$. Fig. 4C, D, upper panels).
280 Furthermore, such sex difference in microbiota age were not affected when we applied men's
281 model to women data (Fig 4C, D, lower panels). Overall, our results indicate that the
282 regressions can explain only 4.8-5.0 % of the variance in chronological age of unrelated healthy
283 adults in the sex-stratified groups from the US cohort.

284 Likewise, in the UK cohort, we found higher microbiota age of women than that of men
285 (from women to men: $p= 0.001401$; from men to women: $p= 1.093e-05$, Wilcoxon rank-sum test;
286 Fig. 4E, F) using 1613 SVs in either women or men's microbiota for building and applying RF
287 models. In addition, we observed significant or borderline significant differences in relative
288 microbiota age between sexes in young (from women to men: $p= 0.1387$; from men to women:
289 $p= 0.01376$. Fig. 4G, H) and middle-aged (from women to men: $p= 0.0001719$; from men to
290 women: $p= 0.05378$. Fig. 4G, H).

291 In the Colombian cohort we used 1074 SVs shared between sexes to build the RF
292 model; similar yet non-significant trends were observed between microbiota age and sex in the
293 non-stratified analyses (from women to men: $p= 0.1103$; from men to women: $p= 0.9997$,
294 Wilcoxon rank-sum test; Fig. 4I, J), and in the young (from women to men: $p= 0.1546$; from men
295 to women: $p= 0.2519$. Fig. 4K, L), and middle-aged groups (from women to men: $p= 0.1435$;
296 from men to women: $p= 0.8326$. Fig. 4K, L). This is likely due to the smaller sample size of this
297 cohort. We used 1279 SVs shared between sexes to build the RF models in the Chinese cohort,
298 the association between microbiota age and sex in was not consistent when we cross-tested
299 models (from women to men: $p= 0.4248$; from men to women: $p= 2.422e-06$. Fig. 4M, N). We
300 did not observe significant associations in the young group (from women to men: $p= 0.1249$;
301 from men to women: $p= 0.01444$. Fig. 4O, P), whereas in the middle-aged we observed sex-
302 dependent difference of microbiota age and such differences are consistent in the cross-
303 application of the models (from women to men: $p= 0.03222$; from men to women: $p= 7.612e-12$.
304 Fig. 4O, P).

305 306 **Discussion**

307
308 In this study, we analyzed the association of gut microbial alpha diversity with age and sex in
309 three large cross-sectional cohorts encompassing four distinct human populations with a focus
310 on gut bacteria of healthy adults. Our analyses indicate that age is positively associated with gut
311 bacterial diversity in men and women, with greater diversity in women than men. Notably, this
312 association occurs in young, but not middle-aged, adults. Consistent with these findings,
313 predicted microbiota age varied based on sex with stronger effects seen in young adults. It is
314 worth underscoring that while we did not observe these patterns in all studied cohorts, it was
315 widespread, robust to technical differences, and the alpha diversity observations were not
316 affected by the cardiometabolic health of the host nor disrupted by antibiotic consumption.

317 These findings provide new insights into the development of the human gut microbiome during
318 the course of life with regards to both age and sex, and emphasize the importance of including
319 these factors as covariates in analyses of the human gut microbiota.

320 While the most dramatic change in gut microbiota diversity occurs in early childhood
321 (Koenig et al., 2011; Yatsunenکو et al., 2012), its increase in adulthood has also been reported
322 (Odamaki et al., 2016). In the cohorts in which the pattern was present, we observed an
323 increase in alpha diversity measures in young adults; however, this trend halted around age 40
324 (Figs 1, S1). This agrees with a previous report, in which no significant differences in alpha
325 diversity were found between middle-aged and elderly subjects (Biagi et al., 2010). Interestingly,
326 the relationship between age and diversity was also linked with sex. Multiple studies have
327 reported differences in the diversity and composition of the gut microbiota between female and
328 male mice, which appear to be associated with a sex bias in the incidence of specific diseases,
329 such as type 1 diabetes (Markle et al., 2013; Yurkovetskiy et al., 2013), rheumatoid arthritis
330 (Gomez et al., 2012), and anxiety (Bridgewater et al., 2017); sex-by-diet interactions have also
331 been reported (Org et al., 2016). While differences in alpha diversity between males and
332 females were reported in humans and mice, we showed that the association between sex and
333 alpha diversity was stronger in young adults compared to middle-aged adults. In agreement with
334 our results, no differences in alpha diversity were observed between women and men in a
335 recent study in which the mean age of participants was 60 years (Haro et al., 2016).

336 One of the most intriguing findings was the difference in gut microbiota richness between
337 the sexes in young adults. This sex-dependent discrepancy suggests that women may enter
338 adulthood with a more diverse gut microbiota, which plateaus to the same levels in both sexes
339 by approximately age 40. The establishment of different microbial communities in males and
340 females may be mediated by sex hormones: female mice show a significant increase in alpha
341 diversity during puberty (Kelley et al., 2016), and differences in the composition of the
342 microbiota increase with age, but are eliminated by male castration (Yurkovetskiy et al., 2013).
343 While little is known about the maturation of the human gut microbiota during puberty, we
344 speculate that the differential hormonal milieu between women and men, and the earlier timing
345 of puberty in women, may result in a more rapid diversification of the gut microbiota in women
346 and that men only achieve the same level of diversification by middle age. Since our findings
347 are based on cross-sectional data and cannot provide causal inference to test this hypothesis,
348 future longitudinal studies that take into account factors such as steroid hormonal levels, age
349 during different stages of puberty, contraceptive consumption, and pregnancy are needed to
350 comprehend long-term trajectories of human gut microbial diversity.

351 While 3 of the 4 cohorts had an association between age, sex and microbial alpha
352 diversity, the Chinese cohort did not (Figs 1, S1), indicating that these associations are a
353 widespread but not universal feature of the human gut microbiota. The overall alpha diversity of
354 this cohort, as measure by SV and the Shannon index, was lower than the other three cohorts in
355 terms of SV. We also note that the exclusion criteria of this population was not the same as the
356 other studies, with only a one-month antibiotic exclusion (versus 1 year) and no stated exclusion
357 of participants with diabetes or inflammatory bowel disease (He et al. 2018).

358 The striking similarity among the US, UK and Colombian cohorts with regards to age and
359 sex-dependent effects on microbial biodiversity arose despite different geographical origins,
360 sample sizes and collection protocols of the studies. Moreover, we also found no apparent

361 effect of antibiotic use (US or UK; Fig. 2) or cardiometabolic health (Colombia; Fig. 3) on the
362 observed pattern in these cohorts, suggesting that the influence of age and sex on the
363 microbiota may be similar in other ethnic and cultural groups, beyond the influence of
364 cardiometabolic disease and antibiotics consumption. Nevertheless, similar large-scale
365 population studies should be performed or reanalysed to determine the extent to which our
366 results are generalizable to other populations, particularly in light of the Chinese cohort. Indeed,
367 the contrast between the UK, US and Colombia cohorts compared to the Chinese cohort
368 highlights the power of using large datasets and comparative analyses across cohorts to
369 uncover subtle patterns and reveal novel insights not discernible in smaller studies. This is of
370 critical importance given the plausibility of population-specific disease signatures of the
371 microbiome (He et al., 2018).

372

373 **Acknowledgements**

374

375 Data acquisition of the Colombian cohort was funded by Grupo Empresarial Nutresa, Dinámica
376 IPS and EPS SURA. NTM was supported by the National Heart, Lung, and Blood Institute of the
377 National Institutes of Health under Award Number K01HL141589, and by grants from the Mid-
378 Atlantic Nutrition Obesity Research Center (P30DK072488) and the Foundation for Gender
379 Specific Medicine. VGT was supported by the National Institute of Child Health and Human
380 Development through a cooperative agreement as part of the National Centers for Translational
381 Research in Reproduction and Infertility (P50 HD012303). STK and VGT received support from
382 the Max Planck Institute for Developmental Biology in Tübingen. This work is supported by IBM
383 Research AI through the AI Horizons Network and the UC San Diego Center for Microbiome
384 Innovation. The content is solely the responsibility of the authors and does not necessarily
385 represent the official views of the National Institutes of Health. Some authors of this work
386 collaborate through the Microbiome & Health Network.

387

388 **Competing interests**

389

390 While engaged in the research project, JSE was employed by a food company. JdIC-Z, STK,
391 YC, NTM, REL, SH, ADS, RK, DM and VGT had no competing interests. The funders of this
392 work had no role in the study design, the collection, analysis or interpretation of the data, the
393 writing of the report or the decision to submit the paper for publication.

394

395 **References**

- 396 Amir, A., McDonald, D., Navas-Molina, J.A., Kopylova, E., Morton, J.T., Zech Xu, Z., Kightley,
397 E.P., Thompson, L.R., Hyde, E.R., Gonzalez, A., Knight, R., 2017. Deblur Rapidly Resolves
398 Single-Nucleotide Community Sequence Patterns. *mSystems* 2.
399 Biagi, E., Nylund, L., Candela, M., Ostan, R., Bucci, L., Pini, E., Nikkila, J., Monti, D., Satokari,
400 R., Franceschi, C., Brigidi, P., De Vos, W., 2010. Through ageing, and beyond: gut
401 microbiota and inflammatory status in seniors and centenarians. *PLoS One* 5, e10667.
402 Bolyen, E., Rideout, J.R., Dillon, M.R., Bokulich, N.A., Abnet, C., Al-Ghalith, G.A., Alexander,
403 H., Alm, E.J., Arumugam, M., Asnicar, F., Bai, Y., Bisanz, J.E., Bittinger, K., Brejnrod, A.,
404 Brislawn, C.J., Titus Brown, C., Callahan, B.J., Caraballo-Rodríguez, A.M., Chase, J.,
405 Cope, E., Da Silva, R., Dorrestein, P.C., Douglas, G.M., Durall, D.M., Duvall, C.,

- 406 Edwardson, C.F., Ernst, M., Estaki, M., Fouquier, J., Gauglitz, J.M., Gibson, D.L.,
407 Gonzalez, A., Gorlick, K., Guo, J., Hillmann, B., Holmes, S., Holste, H., Huttenhower, C.,
408 Huttley, G., Janssen, S., Jarmusch, A.K., Jiang, L., Kaehler, B., Kang, K.B., Keefe, C.R.,
409 Keim, P., Kelley, S.T., Knights, D., Koester, I., Kosciulek, T., Kreps, J., Langille, M.G.I.,
410 Lee, J., Ley, R., Liu, Y.-X., Lofffield, E., Lozupone, C., Maher, M., Marotz, C., Martin, B.,
411 McDonald, D., McIver, L.J., Melnik, A.V., Metcalf, J.L., Morgan, S.C., Morton, J., Naimey,
412 A.T., Navas-Molina, J.A., Nothias, L.F., Orchanian, S.B., Pearson, T., Peoples, S.L.,
413 Petras, D., Preuss, M.L., Pruesse, E., Rasmussen, L.B., Rivers, A., Michael S Robeson,
414 I.I., Rosenthal, P., Segata, N., Shaffer, M., Shiffer, A., Sinha, R., Song, S.J., Spear, J.R.,
415 Swafford, A.D., Thompson, L.R., Torres, P.J., Trinh, P., Tripathi, A., Turnbaugh, P.J., Ul-
416 Hasan, S., van der Hoof, J.J.J., Vargas, F., Vázquez-Baeza, Y., Vogtmann, E., von Hippel,
417 M., Walters, W., Wan, Y., Wang, M., Warren, J., Weber, K.C., Williamson, C.H.D., Willis,
418 A.D., Xu, Z.Z., Zaneveld, J.R., Zhang, Y., Knight, R., Gregory Caporaso, J., 2018. QIIME 2:
419 Reproducible, interactive, scalable, and extensible microbiome data science (No.
420 e27295v1). PeerJ Preprints.
- 421 Bridgewater, L.C., Zhang, C., Wu, Y., Hu, W., Zhang, Q., Wang, J., Li, S., Zhao, L., 2017.
422 Gender-based differences in host behavior and gut microbiota composition in response to
423 high fat diet and stress in a mouse model. *Sci. Rep.* 7, 10776.
- 424 de la Cuesta-Zuluaga, J., Corrales-Agudelo, V., Velásquez-Mejía, E.P., Carmona, J.A., Abad,
425 J.M., Escobar, J.S., 2018. Gut microbiota is associated with obesity and cardiometabolic
426 disease in a population in the midst of Westernization. *Sci. Rep.* 8, 11356.
- 427 Falony, G., Joossens, M., Vieira-Silva, S., Wang, J., Darzi, Y., Faust, K., Kurilshikov, A.,
428 Bonder, M.J., Valles-Colomer, M., Vandeputte, D., Tito, R.Y., Chaffron, S., Rymenans, L.,
429 Verspecht, C., De Sutter, L., Lima-Mendez, G., Dhoe, K., Jonckheere, K., Homola, D.,
430 Garcia, R., Tigchelaar, E.F., Eeckhaut, L., Fu, J., Henckaerts, L., Zernakova, A.,
431 Wijmenga, C., Raes, J., 2016. Population-level analysis of gut microbiome variation.
432 *Science* 352, 560–564.
- 433 Foster, K.R., Schluter, J., Coyte, K.Z., Rakoff-Nahoum, S., 2017. The evolution of the host
434 microbiome as an ecosystem on a leash. *Nature* 548, 43–51.
- 435 Gilbert, J.A., Quinn, R.A., Debelius, J., Xu, Z.Z., Morton, J., Garg, N., Jansson, J.K., Dorrestein,
436 P.C., Knight, R., 2016. Microbiome-wide association studies link dynamic microbial
437 consortia to disease. *Nature* 535, 94–103.
- 438 Gomez, A., Luckey, D., Yeoman, C.J., Marietta, E.V., Berg Miller, M.E., Murray, J.A., White,
439 B.A., Taneja, V., 2012. Loss of sex and age driven differences in the gut microbiome
440 characterize arthritis-susceptible 0401 mice but not arthritis-resistant 0402 mice. *PLoS One*
441 7, e36095.
- 442 Guzman-Castaneda, S.J., Ortega-Vega, E.L., de la Cuesta-Zuluaga, J., Velasquez-Mejia, E.P.,
443 Rojas, W., Bedoya, G., Escobar, J.S., 2018. Gut microbiota composition explains more
444 variance in the host cardiometabolic risk than genetic ancestry. *bioRxiv*.
- 445 Haro, C., Rangel-Zúñiga, O.A., Alcalá-Díaz, J.F., Gómez-Delgado, F., Pérez-Martínez, P.,
446 Delgado-Lista, J., Quintana-Navarro, G.M., Landa, B.B., Navas-Cortés, J.A., Tena-
447 Sempere, M., Clemente, J.C., López-Miranda, J., Pérez-Jiménez, F., Camargo, A., 2016.
448 Intestinal Microbiota Is Influenced by Gender and Body Mass Index. *PLoS One* 11,
449 e0154090.
- 450 He, Y., Wu, W., Zheng, H.-M., Li, P., McDonald, D., Sheng, H.-F., Chen, M.-X., Chen, Z.-H., Ji,
451 G.-Y., Zheng, Z.-D.-X., Mujagond, P., Chen, X.-J., Rong, Z.-H., Chen, P., Lyu, L.-Y., Wang,
452 X., Wu, C.-B., Yu, N., Xu, Y.-J., Yin, J., Raes, J., Knight, R., Ma, W.-J., Zhou, H.-W., 2018.
453 Regional variation limits applications of healthy gut microbiome reference ranges and
454 disease models. *Nat. Med.*
- 455 Hopkins, M.J., Sharp, R., Macfarlane, G.T., 2002. Variation in human intestinal microbiota with
456 age. *Dig. Liver Dis.* 34 Suppl 2, S12–8.

- 457 Kelley, S.T., Skarra, D.V., Rivera, A.J., Thackray, V.G., 2016. The Gut Microbiome Is Altered in
458 a Letrozole-Induced Mouse Model of Polycystic Ovary Syndrome. *PLoS One* 11,
459 e0146509.
- 460 Koenig, J.E., Spor, A., Scalfone, N., Fricker, A.D., Stombaugh, J., Knight, R., Angenent, L.T.,
461 Ley, R.E., 2011. Succession of microbial consortia in the developing infant gut microbiome.
462 *Proc. Natl. Acad. Sci. U. S. A.* 108 Suppl 1, 4578–4585.
- 463 Kozik, A.J., Nakatsu, C.H., Chun, H., Jones-Hall, Y.L., 2017. Age, sex, and TNF associated
464 differences in the gut microbiota of mice and their impact on acute TNBS colitis. *Exp. Mol.*
465 *Pathol.* 103, 311–319.
- 466 Lloyd-Price, J., Mahurkar, A., Rahnavard, G., Crabtree, J., Orvis, J., Hall, A.B., Brady, A.,
467 Creasy, H.H., McCracken, C., Giglio, M.G., McDonald, D., Franzosa, E.A., Knight, R.,
468 White, O., Huttenhower, C., 2017. Strains, functions and dynamics in the expanded Human
469 Microbiome Project. *Nature* 550, 61–66.
- 470 Maffei, V.J., Kim, S., Blanchard, E., 4th, Luo, M., Jazwinski, S.M., Taylor, C.M., Welsh, D.A.,
471 2017. Biological Aging and the Human Gut Microbiota. *J. Gerontol. A Biol. Sci. Med. Sci.*
472 72, 1474–1482.
- 473 Mariat, D., Firmesse, O., Levenez, F., Guimarães, V., Sokol, H., Doré, J., Corthier, G., Furet, J.-
474 P., 2009. The Firmicutes/Bacteroidetes ratio of the human microbiota changes with age.
475 *BMC Microbiol.* 9, 123.
- 476 Markle, J.G.M., Frank, D.N., Mortin-Toth, S., Robertson, C.E., Feazel, L.M., Rolle-Kampczyk,
477 U., von Bergen, M., McCoy, K.D., Macpherson, A.J., Danska, J.S., 2013. Sex differences in
478 the gut microbiome drive hormone-dependent regulation of autoimmunity. *Science* 339,
479 1084–1088.
- 480 McDonald, D., Hyde, E., Debelius, J.W., Morton, J.T., Gonzalez, A., Ackermann, G., Aksenov,
481 A.A., Behsaz, B., Brennan, C., Chen, Y., DeRight Goldasich, L., Dorrestein, P.C., Dunn,
482 R.R., Fahimipour, A.K., Gaffney, J., Gilbert, J.A., Gogul, G., Green, J.L., Hugenholtz, P.,
483 Humphrey, G., Huttenhower, C., Jackson, M.A., Janssen, S., Jeste, D.V., Jiang, L., Kelley,
484 S.T., Knights, D., Kosciulek, T., Ladau, J., Leach, J., Marotz, C., Meleshko, D., Melnik,
485 A.V., Metcalf, J.L., Mohimani, H., Montassier, E., Navas-Molina, J., Nguyen, T.T., Peddada,
486 S., Pevzner, P., Pollard, K.S., Rahnavard, G., Robbins-Pianka, A., Sangwan, N.,
487 Shorenstein, J., Smarr, L., Song, S.J., Spector, T., Swafford, A.D., Thackray, V.G.,
488 Thompson, L.R., Tripathi, A., Vázquez-Baeza, Y., Vrbancac, A., Wischmeyer, P., Wolfe, E.,
489 Zhu, Q., American Gut Consortium, Knight, R., 2018. American Gut: an Open Platform for
490 Citizen Science Microbiome Research. *mSystems* 3.
- 491 Odamaki, T., Kato, K., Sugahara, H., Hashikura, N., Takahashi, S., Xiao, J.-Z., Abe, F., Osawa,
492 R., 2016. Age-related changes in gut microbiota composition from newborn to centenarian:
493 a cross-sectional study. *BMC Microbiol.* 16, 90.
- 494 Org, E., Mehrabian, M., Parks, B.W., Shipkova, P., Liu, X., Drake, T.A., Lusi, A.J., 2016. Sex
495 differences and hormonal effects on gut microbiota composition in mice. *Gut Microbes* 7,
496 313–322.
- 497 Sinha, T., Vich Vila, A., Garmeaeva, S., Jankipersadsing, S.A., Imhann, F., Collij, V., Bonder,
498 M.J., Jiang, X., Gurry, T., Alm, E.J., D'Amato, M., Weersma, R.K., Scherjon, S., Wijmenga,
499 C., Fu, J., Kurilshikov, A., Zhernakova, A., 2018. Analysis of 1135 gut metagenomes
500 identifies sex-specific resistome profiles. *Gut Microbes* 1–9.
- 501 Wallis, A., Butt, H., Ball, M., Lewis, D.P., Bruck, D., 2016. Support for the Microgenderome:
502 Associations in a Human Clinical Population. *Sci. Rep.* 6, 19171.
- 503 Wallis, A., Butt, H., Ball, M., Lewis, D.P., Bruck, D., 2017. Support for the microgenderome
504 invites enquiry into sex differences. *Gut Microbes* 8, 46–52.
- 505 Yatsunenkov, T., Rey, F.E., Manary, M.J., Trehan, I., Dominguez-Bello, M.G., Contreras, M.,
506 Magris, M., Hidalgo, G., Baldassano, R.N., Anokhin, A.P., Heath, A.C., Warner, B., Reeder,
507 J., Kuczynski, J., Caporaso, J.G., Lozupone, C.A., Lauber, C., Clemente, J.C., Knights, D.,

508 Knight, R., Gordon, J.I., 2012. Human gut microbiome viewed across age and geography.
509 Nature 486, 222–227.
510 Yurkovetskiy, L., Burrows, M., Khan, A.A., Graham, L., Volchkov, P., Becker, L., Antonopoulos,
511 D., Umesaki, Y., Chervonsky, A.V., 2013. Gender bias in autoimmunity is influenced by
512 microbiota. Immunity 39, 400–412.

513

514
515
516
517
518
519

Table 1. General characteristics of the participants of the included cohorts. Values given as mean (SD)

	Age group	Young (20 - 45)		Middle Age (46 - 69) ¹	
	Sex	Female	Male	Female	Male
AGP - US	N	627	644	734	583
	Age	34.6 (6.79)	33.76 (6.61)	56.13 (6.37)	57.13 (6.41)
	SV richness	113.81 (33.04)	109.95 (31.51)	120.40 (34.63)	119.0 (33.07)
	Shannon Index	4.87 (0.83)	4.83 (0.80)	4.98 (0.89)	5.01 (0.78)
AGP - UK	N	195	173	344	224
	Age	35.9 (6.02)	36.4 (6.32)	56.45 (6.68)	57.75 (6.85)
	SV richness	132.0 (31.69)	122.60 (32.38)	142.30 (36.27)	139.10 (36.23)
	Shannon Index	5.27 (0.69)	5.05 (0.92)	5.36 (0.83)	5.29 (0.80)
China	N	946	670	1826	1521
	Age	35.16 (6.73)	34.88 (7.07)	56.6 (6.59)	57.36 (6.75)
	SV richness	101.8 (27.90)	99.66 (26.48)	99.41 (28.67)	101.4 (28.50)
	Shannon Index	4.47 (0.85)	4.40 (0.84)	4.36 (0.93)	4.35 (0.95)
Colombia	N	143	133	83	78
	Age	33.83 (7.21)	34.21 (6.98)	52.48 (4.14)	52.90 (4.42)
	SV richness	120.41 (30.21)	110.71 (31.06)	123.33 (32.75)	116.13 (33.95)

	Shannon index	4.60 (1.05)	4.48 (1.12)	4.73 (0.99)	4.45 (1.13)
	Cardiometabolic risk scale	-1.14 (3.07)	0.64 (3.67)	-0.36 (3.06)	1.39 (2.71)

520 ¹ Age of Colombian individuals ranged from 20 to 62 years

521

522

523







