

1 Ancient dental calculus reveals oral microbiome shifts
2 associated with lifestyle and disease in Great Britain

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44 **Abstract**

45 The prevalence of chronic, noncommunicable diseases has risen sharply in recent
46 decades, especially in industrialized countries. While several studies implicate the
47 microbiome in this trend, few have examined the evolutionary history of industrialized
48 microbiomes. Here, we sampled 235 ancient dental calculus samples from individuals living
49 in Great Britain (~2200 BCE to 1853 CE), including 127 well-contextualized London adults.
50 We reconstructed their microbial history spanning the transition to industrialization. After
51 controlling for oral geography and technical biases, we identified multiple oral microbial
52 communities that co-existed in Britian for millennia, including a community associated with
53 *Methanobrevibacter*, an anaerobic Archaea not prevalent in the oral microbiome of modern
54 industrialized societies. Calculus analysis suggests that oral hygiene contributed to oral
55 microbiome composition, while microbial functions reflected past differences in diet,
56 specifically in dairy and carbohydrate consumption. In London samples,
57 *Methanobrevibacter*-associated microbial communities are linked with skeletal markers of
58 systemic diseases (e.g., periostitis and joint pathologies), and their disappearance is consistent
59 with temporal shifts, including the arrival of the Second Plague Pandemic. This suggests pre-
60 industrialized microbiomes were more diverse than previously recognized, enhancing our
61 understanding of chronic, noncommunicable disease origins in industrialized populations.

62 **Main Text**

63

64 ***Introduction***

65 Modern, industrialized microbiomes are linked to a wide-range of noncommunicable,
66 chronic diseases, including obesity, cardiovascular disease, allergies, and poor mental
67 health^{1,2}, which are increasing rapidly in industrialized countries and are predicted to rise in
68 low- and middle-income countries in the future^{3,4}. As such, determining the evolutionary
69 background of these microbial communities is critical to understanding the origins and
70 aetiologies of these diseases. To date, the origins and evolution of industrialized microbiomes
71 are primarily investigated by examining so-called “pre-industrialized” microbiomes of other
72 primates or extant Indigenous peoples who practise traditional subsistence lifeways, (i.e.,
73 hunting and foraging)⁵⁻⁹. Such research has suggested that shifts in diet (e.g., reductions in
74 dietary fibre⁸) and the loss of microbes (e.g., *Helicobacter pylori*) have shaped industrialized
75 gut microbiomes⁵, alongside changes in environmental and social factors¹⁰. Studies tracking
76 gut microbiomes of immigrants to industrialized countries, such as the United States of
77 America, have similarly demonstrated a decrease in diversity and a loss of certain species
78 upon the adoption of ‘Western’ lifestyles^{11,12}, confirming that industrialization has significant
79 impacts on the human gut microbiome. As a response, scientists have called for the
80 biobanking of Indigenous people’s microbes before those microbes become extinct¹³.

81 Despite these findings, the extent and rate of microbial extirpations in industrialized
82 societies remain poorly understood, as the approaches used to describe pre-industrialized
83 microbiota are problematic. First, each population has a unique evolutionary history with
84 distinct genetics, environments, diets and selection pressures that shape its microbiome in
85 unique ways¹⁴. Consequently, modern non-industrialized populations or immigrants may not
86 accurately reflect the microbes that existed in the ancestors of industrialized peoples
87 today^{15,16}. Second, this research places unnecessary responsibilities and obligations on
88 Indigenous communities to participate in microbiome research, where the benefits of these
89 studies may not directly serve Indigenous peoples¹⁷. Therefore, a more direct path towards
90 reconstructing pre-industrialized human microbiomes is needed. One such approach is to
91 utilise the available bioarchaeological record of communities that predate industrialized
92 populations through the analysis of ancestral archaeological human remains. Although this
93 approach involves a number of complex challenges in recovering gut microbiomes^{18,19},
94 reconstructing ancient oral microbiomes preserved within calcified dental plaque (i.e.,
95 calculus) is an established way of tracing past oral microbial histories^{20,21}.

96 **Results**

97 **Filtering and Authentication**

98 We performed the largest ancient dental calculus study conducted to date (n=235 samples
99 assessed), reconstructing authenticated oral microbiota using shotgun metagenomics from
100 183 pre-industrialized individuals who were excavated across 27 archaeological sites in
101 England and Scotland (Figure 1; Table S1) from ~2,200 BCE to 1853 CE, to directly describe
102 the history of a pre-industrialized population's microbiome. These samples originate from
103 eight geographic regions and include individuals who resided in Britain before Roman
104 colonization through to the 'Industrial Revolution' (Supplemental Text (Archaeological
105 context and sample descriptions); Table S1). We used a multi-tiered assessment procedure to
106 authenticate and control for contamination in this data set (Supplemental Text (Data
107 processing, quality filtering, and authentication); summarized in Figure S3; Tables S2, S3,
108 S4, S5, S13). First, we only included high quality samples with >100,000 taxonomically
109 assigned sequences²² and more than five phyla²⁰. We authenticated ancient DNA
110 fragmentation with a novel, reference-free DNA damage program called ChangePoint²³
111 (Table S5) and the gold-standard, reference-based approach called MapDamage2.0²⁴;
112 damage consistent with these archaeological ages was present in known oral species
113 (*Streptococcus sanguinis*, *Porphyromonas gingivalis*, *Actinomyces oral taxon 414*,
114 *Anaerolineacea bacterium oral taxon 439*, and *Methanobrevibacter oralis*) and less in
115 common contaminant species (*Burkholderia multivorans*, *Comamonas Sestosterone*,
116 *Escherichia coli*, and *Flavobacteriaceae* bacterium; Table S13). We were conservative and
117 limited the effects of potential laboratory and environmental contaminant DNA by removing
118 samples whose microbial composition was similar to that of laboratory controls (Figure S2;
119 Table S2) and conservatively filtering contaminant species identified in environmental and
120 laboratory controls (Figure S4; Table S4). Lastly, we verified the presence of oral taxa from
121 known modern and ancient oral microbiomes using SourceTracker1.0 (MALTx results) and
122 SourceTracker2.0 (MALTn results) (Supplemental Text (data processing, quality filtering,
123 and authentication); average 85% oral; Figure S2 and S13) and confirmed the highly
124 abundant taxa were present in the Human Oral Microbiome Database (HOMD; Figure S13C).

125

126 **Oral Geography Biases**

127 As oral geography (i.e., position within the oral cavity) plays a role in oral microbiome
128 composition²⁵⁻²⁸, we tested and identified oral geography biases in the dataset; calculus
129 sample size and gingival location influenced taxonomic composition in molars, while tooth

130 surface drove compositional variation in incisors (Figure 2A-C; Supplemental Text
131 (Microbial composition analysis). As a result, we stratified our taxonomic and functional data
132 according to tooth type and included oral geography (i.e., tooth type, surface, gingival region,
133 and calculus size) in our statistical analyses (Table S6-S9). As these biases likely reflect
134 biological and ecological differences in the mouth²⁵, these differences attributed to oral
135 geography raise questions about the interpretations of previous paleomicrobiome studies that
136 used calculus samples collected from a mixed dentition²⁹⁻³¹ and suggest that future studies
137 should control for oral geography during sampling and analysis (Figure S18). Overall, 954
138 microbial species were identified across all ancient British calculus samples, predominantly
139 spanning Firmicutes, Actinobacteria, Proteobacteria, and Bacteroidetes phyla (Figure S4).

140

141 **Drivers of Variation**

142 To explore drivers of variation in pre-industrialized oral microbiome composition, we
143 performed a Principal Coordinates Analysis (PCoA) ordination of Bray-Curtis dissimilarities
144 with BiPlots (Figure 3A and S5A) using microbial genera in the samples. We observed a ‘U’
145 shaped curve indicative of distinct ecologies³² (Figure 3A; Axis 1=41.25% variation; Table
146 S10), and the Biplots indicated that *Methanobrevibacter* and *Streptococcus* genera were
147 associated with the 41.2% of the variation explained by Axis 1, while *Actinomyces*-
148 dominated communities drove variation on Axis 2 (13.8%; Figure 3A). As such, we grouped
149 the samples according to whether or not *Methanobrevibacter*, *Streptococcus*, or *Actinomyces*
150 genera were most dominant in each sample. We then compared the two communities on the
151 extremes of Axis 1 (i.e., *Streptococcus*- and *Methanobrevibacter*-associated) to assess major
152 factors that drive oral microbial diversity (Figure 3A). *Streptococcus*- and
153 *Methanobrevibacter*-associated samples contained distinct community assemblages
154 (Dominant category; $R^2 \geq 0.20$, $p < 0.05$; Table S12). Co-occurrence analysis of the
155 *Streptococcus*- or *Methanobrevibacter*-associated communities using CCLasso positively
156 associated *Streptococcus* with *Leptotrichia*, *Neisseria*, *Gemella*, *Capnocytophaga*,
157 *Granulicatella*, *Lautropia*, *Kingella*, *Aggregatibacter*, *Lachnoanaerobaculum*, and *Rothia*
158 genera (Figures 3B-C; Table S11), as seen in modern industrialized oral microbiomes from
159 Spain (Figure S6). In contrast, *Methanobrevibacter* positively co-occurred with genera not
160 often described in the industrialized oral cavity, including *Methanosphaera*, *Peptoniphilus*,
161 *Anaerofustis*, *Syntrophomonas*, *Shuttleworthia*, *Subdoligranulum*, *Pseudoramibacter*,

162 *Synergistes*, *Hungatella*, and *Butyrivibrio* taxa (Figures 3B-C; Table S11). Several different
163 oral *Methanobrevibacter* species have now been described in ancient mouths³³, and at least
164 three of the co-occurring genera have been previously characterized in the mouth³⁴⁻³⁶ and not
165 as contaminants^{20,26,30}. We confirmed via a literature review that species within these co-
166 occurring genera can cohabitate with *Methanobrevibacter* oral species, as all are anaerobic
167 and can produce metabolic by-products that support methanogenesis³⁷. However, this
168 *Methanobrevibacter*-associated community has not yet been described in studies of modern
169 dental calculus^{20,31,38}, suggesting that a *Methanobrevibacter*-associated community may
170 represent a unique oral microbial ecology not typically found in modern industrialized
171 societies.

172 To explore the origins of these two microbial communities, we tested whether
173 physiological, cultural, and temporal factors previously thought to drive ancient oral
174 microbiome composition were associated with this signal in ancient British microbiomes³⁹.
175 Demographic variables (i.e., sex and age), broad cultural classifications (i.e., religion, class,
176 or urban/rural locations; Table S1), or major biocultural or socio-political events (e.g., Civil
177 War or plague outbreaks, such as the Second Plague Pandemic, also known as the Black
178 Death (caused by *Yersinia pestis*); Table S1) did not explain significant levels of taxonomic
179 or functional compositional variation across Great Britain (ADONIS; $p > 0.05$; Table S12). A
180 mild association between the location where individuals were buried (i.e., cemetery) and
181 microbial genera composition was observed (ADONIS; $R^2 = 0.158$; $p = 0.031$; Table S12), but
182 this was not true when examining the data at the species level (ADONIS of contaminant
183 species-filtered data; $p > 0.05$; Table S12). Surprisingly, these findings suggest that these
184 large scale cultural and social factors that occurred across Britain over 2,200 years were not
185 significantly drivers of oral microbiome composition at a population scale in this data set.
186

187 **Associations with Oral Health**

188 We next examined if these microbial communities were linked to known signatures of
189 oral disease, as *Methanobrevibacter* taxa have been linked to severe periodontitis in modern
190 populations⁴⁰. As indicated by an ADONIS test ($p < 0.05$), oral microbiome composition in
191 all individuals was not linked to the occurrence of periodontal disease, nor other known oral
192 pathologies (i.e., caries or apical abscesses; Table S12). Surprisingly, species and functions
193 linked to periodontal disease in modern populations (e.g., *Porphyromonas gingivalis* and
194 *Tanerella forsythia*) were more likely to be found in *Streptococcus*-associated communities
195 than those dominated by *Methanobrevibacter* (Table S13), suggesting that the modern

196 aetiology of industrial-age periodontal disease may in fact originate from the *Streptococcus*-
197 associated communities. However, oral microbiome composition was directly linked with
198 size of the calculus sample analysed (Figure 2B; Table S6-S9). While it would be reasonable
199 to infer that *Methanobrevibacter*-associated communities may thrive within larger,
200 potentially more mature calculus deposits, consistent with the anaerobic requirements of
201 these taxa, we did not find this to be the case. The separation of samples into *Streptococcus*-
202 or *Methanobrevibacter*-associated communities did not explain calculus sample size (adonis;
203 $p=0.101$), nor were the size of calculus samples driven by *Methanobrevibacter*-associated
204 species. Rather, *Streptococcus* community-associated taxa (based on the correspondence
205 analysis in Table S11), including *Gemella* and *Lautropia*, were associated with larger sample
206 sizes (ALDEx2; Figure S17). Nevertheless, modern oral hygiene practices can reduce dental
207 plaque and calculus formation^{41,42} and lead to smaller deposits, so it is possible that
208 compositional shifts in ancient British communities are linked to dental hygiene practices.

209

210 **Exploring Diets**

211 As dietary changes are proposed to be a main driver of oral microbiome evolution
212 through time^{20,30,39}, we further explored if differences in diet could underpin these two
213 distinct microbial ecologies. Direct dietary DNA signals were explored in six deeply
214 sequenced calculus samples (i.e., >100 million sequences per sample; three samples each
215 from *Streptococcus*-associated or *Methanobrevibacter*-associated communities), but after
216 careful consideration^{43,44}, no verifiable DNA fragments could be robustly confirmed from
217 either plant or non-host animals. As oral microbes in dental plaque can ferment sugars, starch
218 molecules, and amino acids in the mouth⁴⁵, we then developed a novel approach to explore if
219 indirect dietary signals were present. We assembled a list of microbial genetic functional
220 differences linked to dietary changes in the gut^{8,20,46,47}, as a proxy for predicting broad dietary
221 differences. We included 42 amino acid metabolism functions linked to either carnivorous or
222 herbivorous diets⁴⁶; 17 functions linked to high or low-dietary fibre digestion⁸; 124
223 carbohydrate metabolism gene families; and 30 lactose and galactose metabolism functions
224 linked to milk consumption (Table S14). We first validated this approach by examining the
225 presence of these microbial functions in calculus from a modern, industrialized Spanish
226 population (Table S1). Our results were consistent with an omnivorous diet with high sugar
227 (e.g., lactate fermentation, fructose utilization, galactose degradation, and glucose utilization)
228 and low dietary fibre intake (e.g., glycan degradation) (Figure 4; Table S15). Notably,
229 microbial functions associated with dairy consumption (i.e., beta-galactosidase or lactase; EC

230 3.2.1.23) were highly abundant in these modern human oral microbiomes (Figure 4; Table
231 S15).

232 In our ancient dataset, we identified 81.0% (34 of 42) of the amino acid metabolism
233 pathways associated with herbivory or carnivory in ancient samples (Table S15). Whilst 88%
234 were significantly more abundant in one of the two microbial communities (Figure 4, Figure
235 S7), both microbiomes possessed functions consistent with an omnivorous diet (Figure 4,
236 Figure S8). *Streptococcus*-associated communities contained more microbial functions
237 significantly linked with low-fibre (70% of the 16 identified fibre digestion functions;
238 galactose metabolism, glycosphingolipid biosynthesis, and glycan degradation; Figure 4;
239 Figure S9) and high carbohydrate diets (46.8% of the 124 carbohydrate metabolism
240 associated genes, compared to 22.6% in *Methanobrevibacter*-associated communities),
241 including pathways linked to fructose, sucrose, trehalose, mannose, beta-glucosides, and
242 maltose metabolism (Figure 4; Figure S10). In contrast, *Methanobrevibacter*-associated
243 communities were enriched for functions linked to methanogenesis, gluconeogenesis, and
244 xylose utilization (Figure 4; Figure S10). Lastly, *Streptococcus*-associated individuals
245 showed increased abundances of microbial functions linked to dairy consumption (26.7% of
246 lactose metabolism genes were significantly enriched compared to 6.7% in
247 *Methanobrevibacter*-associated communities; Figure 4 and S12), including a significant
248 enrichment in alpha and beta galactosidases, similar to observations in modern individuals
249 (Figure S12; Table S15). This observation may reflect differences in dairy consumption or
250 access across Britain, which is consistent with the presence of milk proteins in only one-third
251 of Medieval calculus samples from Britain (800 BCE to 1895 CE)⁴⁸, even though dairy
252 products were widely available⁴⁹. Together, this analysis represents a powerful instrument in
253 a growing toolbox of biomolecular approaches to reconstruct past diets and suggests that past
254 carbohydrate and dairy consumption may be reflected in the oral microbiome of past British
255 populations.

256

257 **London-specific Analyses**

258 As large-scale geographic differences across Great Britain may mask factors that
259 drive oral microbiome variation through time⁴⁹, we further narrowed our analysis to 127
260 medieval and post-medieval (1066 to 1853 CE) individuals from London that have been
261 extensively studied to further explore the origin of these two distinct oral communities, while
262 again controlling for oral geography effects (Table S16-S18). As seen in the above Britain-
263 wide analysis, the physiological or cultural factors considered did not appear to significantly

264 contribute to past Londoners' oral microbiome composition ($p = >0.05$; Table 1). However,
265 the presence of disease, as defined by 14 detailed oral and other systemic health indicators
266 previously recorded on the bones and teeth of the individuals included in this study in the
267 Wellcome Osteological Research Database (WORD), did potentially explain some of the
268 differences in oral microbiome composition. In London, periodontal disease (but not caries,
269 abscesses, or dental developmental defects) was significantly linked to oral microbiome
270 composition ($R^2 > 0.05$; $p < 0.05$; Table 1). Again, microbial species positively associated
271 with periodontal disease were, rather surprisingly, more commonly found in *Streptococcus*-
272 associated communities, rather than *Methanobrevibacter*-associated ones (Table S19).
273 However, the *Methanobrevibacter*-associated communities were associated with the presence
274 of several skeletal markers of systemic disease, including non-specific periostitis, joint
275 porosity, osteophytic lipping, and overall scores for joint pathologies ($R^2 > 0.05$; $p < 0.05$;
276 Table 1). While there could be multiple causes for these skeletal markers, most are thought to
277 be related to inflammatory-associated conditions. Each of these disease-markers was also
278 linked to specific genera within the *Methanobrevibacter*-associated community (Table S19),
279 such as *Methanobrevibacter*, *Eubacterium*, *Pseudoramibacter*, *Mogibacterium*, and
280 *Peptoniphilus* taxa (Table S19). While not all systemic diseases contribute to morphological
281 changes in the skeleton, the association between oral microbiomes and systemic diseases has
282 been clearly demonstrated in modern individuals, often through inflammatory pathways^{50,51}.
283 While cause and effect remain unclear, or may be the result of indirect associations (e.g.,
284 socioeconomic status), this is the first time that ancient microbiomes have been linked to
285 systemic diseases that manifest in the skeleton, and therefore, provides a new model to
286 examine the origins of modern chronic, noncommunicable diseases.

287

288 **Methanobrevibacter Over Time**

289 Lastly, we examine why this distinct *Methanobrevibacter*-associated oral ecology is
290 not commonly found today in industrialized populations by exploring its presence over time.
291 In all of Britain, the *Methanobrevibacter*-associated community was first observed in
292 individuals ~2,200 years ago and was still present in London until at least ~1853 (Figure
293 S10). We then examined compositional shifts over time in just London. Oral microbiome
294 composition significantly shifted across 300- and 400-year intervals ($p = < 0.05$; Table 1), and
295 significantly shifted after the arrival of the Second Plague Pandemic, in London in 1348. The
296 arrival of *Y. pestis* was verified in plague cemeteries (e.g., East Smithfield)⁵² and resulted in
297 the deaths of over 30-50% of Londoners between 1348 to 1351 alone⁵³, changing the

298 population structure and ways of life in the city substantially. As temporal differences can be
299 confounded by taphonomy, we examined these compositional shifts in the context of the
300 Second Plague Pandemic more closely by fitting a Bayesian multinomial logistic-normal
301 linear model to the overall oral microbiome composition from historic London, which
302 included the arrival of the Second Plague Pandemic as a covariate and minimized the impacts
303 of oral geography and cemetery location. Our results show that 10.88% of the total variation
304 in microbiome composition can be explained by temporal changes, including the arrival of
305 the Second Plague Pandemic (95% credible interval: 4.98% to 19.47%), while only 65.41%
306 of that signal could be equally explained by other factors (Supplemental Text (Bayesian
307 modelling)). Additionally, only 1.5% of the variation explained by burial location was
308 attributed to DNA damage patterns (deltaD) associated with oral taxa
309 *Anaerolineaceae*, *Methanobrevibacter oralis*, *Porphyromonas gingivalis*, and *Streptococcus*
310 *sanguinis* (Table S13; Supplemental Text (Bayesian modelling)), suggesting this observation
311 is not driven by taphonomy. While this finding needs further examination, temporal shifts in
312 oral microbiome composition coinciding with the Second Plague Pandemic in London could
313 be the result of disease selection and susceptibility during the pandemic^{54,55}, subsequent
314 advancements in public health and hygiene⁵⁶, dietary shifts, and/or cultural shifts that were a
315 consequence of this significant pandemic on the citizens of London.

316

317 **Discussion**

318 Our study reveals the existence of a now rare or potentially extinct oral microbial
319 ecosystem that was present in British populations over at least 2,200 years alongside other
320 oral microbiome communities. This oral microbial community persisted through major bio-
321 cultural transitions and historically significant socio-political events, only to diminish in
322 recent history – a phenomenon associated with the rise of industrialization. Why this
323 *Methanobrevibacter*-associated community disappeared in Britain or has not yet been
324 described in healthy modern, industrialized societies remains unknown, but reports of broad
325 spread *Methanobrevibacter* species in the ancient calculus literature suggest that this
326 community may have once been widespread³³. Our findings suggest that advancements in
327 modern dentistry (e.g., the routine removal of large calculus deposits and the use of modern
328 oral hygiene products), shifts in dairy and carbohydrate consumption, and medical care may
329 have additionally contributed to its perceived absence today, although further work should
330 explore additional lifestyle changes post-1900s, including migration and nutrition. This
331 finding establishes a new paradigm to explore the foundations and origins of chronic,

332 noncommunicable disease in living populations and opens the door to identify unknown (now
333 extinct) microbial diversity in past, pre-industrialized human populations.

334

335 **Methods**

336 *Sample Information and Collection*

337 For calculus samples obtained from individuals who lived in Britain, access was
338 provided by the Natural History Museum (NHM), Royal College of Surgeons of England,
339 Oxford Archaeology East, and the Aberdeen Museum (Table S1). For samples from historic
340 London, 160 archaeological samples were collected from individuals buried at eight different
341 cemeteries in a 10-square mile section of London (16 km²), which formed a continuous
342 temporal sequence from ~1000 – 1853 CE, from the curated archaeological skeletal remains
343 collection stored at the Museum of London. No statistical methods were used to pre-
344 determine sample sizes but our sample sizes are similar to and generally exceed those
345 reported in previous publications^{20,49}. Detailed information on each sample is provided in
346 Table S1. Samples were handled using sterile procedures as previously outlined²⁰. Intact
347 calculus samples were stored in labelled, sterile, plastic bags and transported to the ancient
348 DNA facility at the Australian Centre for Ancient DNA (ACAD), University of Adelaide,
349 Australia.

350

351 *Decontamination, DNA extraction, and Library Preparation*

352 Careful consideration was given to the risk of laboratory and environmental
353 contamination, as endogenous signals can be easily obscured or misinterpreted due to
354 contaminating microbial DNA^{26,27}. To minimize contamination, samples were processed in
355 an ultra-sterile, specialized ancient DNA laboratory and underwent a decontamination
356 protocol, as previously published³⁹. Samples underwent an in-house, silica-based DNA
357 extraction, as previously described^{20,57,58}. Extraction blank controls (EBCs) were incorporated
358 throughout to monitor laboratory and reagent contamination at a ratio of two EBCs to ten
359 samples, as well as no template controls (NTCs) during the amplification process⁵⁹. Shotgun
360 libraries were generated using a previous protocol²⁰. Samples were sequenced on an Illumina
361 NextSeq using a high output 2 x 150 bp kit. Further details about the methods are available in
362 the Supplemental Text.

363

364 *Bioinformatic and Statistical Analysis*

365 DNA sequences were demultiplexed, trimmed, and merged using AdapterRemoval2.0
366 with a 5 bp overlap⁶⁰. Taxonomic and functional information was derived from analysis-
367 ready reads using MALTx²⁰ against the 2014nr database. Taxonomic comparisons were also
368 completed using MALTn against the 2017 RefSeqGCS database (Supplemental Text (Data
369 processing, quality filtering, and authentication)). Only collapsed reads were used because
370 fragments greater than 300 bp were considered more likely to be modern DNA
371 contamination¹⁹. 14 samples with a Bray-Curtis dissimilarity value > 0.72 (the similarity of
372 negative controls to themselves) in comparison to negative control were excluded. Next, all
373 species identified within the negative control samples were conservatively removed from all
374 samples; genera and higher classifications of data were not filtered. Four samples with
375 <100,000 DNA sequences were also removed, as these are unlikely to capture overall
376 microbial community structures²². We also authenticated the oral signal in our samples using
377 a range of ancient calculus, modern calculus and plaque, soil, and laboratory controls
378 SourceTracker2.0⁶¹, and we verified DNA damage consistent with known ages of samples
379 using both a reference free approach using ChangePoint analysis²³ and the reference based
380 gold-standard approach MapDamage2.0²⁴ against oral and contaminant species
381 (Supplemental Text (Data processing, quality filtering, and authentication)).

382 To identify correlations with metadata and taxonomic data, taxonomic information
383 from modern and ancient samples were exported from MEGAN6 CE and imported into
384 QIIME2 (V2020.2.0)⁶², and singletons were removed. We rarefied the dataset to the
385 maximum number of sequences available (100,000 for all taxa; 60,000 for genera; and
386 30,000 for species per sample). Bray-Curtis dissimilarity was calculated with BiPlots, and the
387 ADONIS test was applied (9999 permutations) to identify factors that shaped beta diversity
388 in the data set. As each ADONIS test incorporates multiple variables, a correction for
389 multiple tests may not be necessary. Nevertheless, we report p-values of $p < 0.05$ as
390 significant, and we highlight which results are also significant when applying a Bonferroni
391 correction to account for multiple ADONIS tests (i.e., p-value of $p < 0.002$) (Table 1). LefSe
392 analysis was conducted to identify specific species that increased in abundance with select
393 metadata fields⁶³. To explore the functional potential of the microbiomes, functional tables
394 were exported from MEGAN6 CE into QIIME2. Amino acid functions matching the Enzyme
395 Commission numbers identified as distinguishing of carnivores and herbivores⁴⁶ were
396 exported. For carbohydrate and dairy metabolism, all Level 4 functional groups were
397 exported. Fiber metabolism functions⁶⁴ were exported from the KEGG database within
398 MEGAN5. ADONIS tests were run on functional data as done with taxonomic data, and

399 LefSE analysis was conducted to identify specific functions that increased in abundance with
400 select metadata fields.

401

402 *Project Outreach*

403 To promote this project and provide ways for non-scientists to engage with this work,
404 we engaged visitors to the Museum of London in conversations during the sampling period of
405 this study. A stall was set-up in the public galleries of the Museum for one afternoon within
406 the five-day sampling visit. The stall consisted of a single table, using skulls and models from
407 the Museum's Centre for Human Bioarchaeology teaching collection, and a conference
408 poster. The teaching collection and poster served to attract attention and trigger conversation.
409 Conversational engagement allowed the public to ask their own questions and query the
410 topics that interested them. Discussions included the active project, background to the field,
411 broader anthropological questions, and discussions of our team member's career path. In
412 doing this, we offered an opportunity to engage with the public and support diverse and
413 active learning in museums, enhancing Science Capital⁶⁵, while promoting the active research
414 and ongoing partnerships of these institutions.

415

416 *Ethics Statement*

417 Ancient human samples are not subject to institutional review board approvals;
418 however, this study was reviewed by the University of Adelaide Human Research Ethics
419 Committee and received approval (H-2012-108).

420

421 *Data Availability*

422 All trimmed and merged DNA sequences (fastq) are available on NCBI's SRA
423 database (BioProject [PRJNA780005](https://www.ncbi.nlm.nih.gov/bioproject/PRJNA780005)). The 2017 NCBI nr database and the 2017 NCBI
424 RefSeq GCS databases were both used in this study. Unmerged reads can be made available
425 upon request.

426

427 *Code Availability*

428 The analysis pipelines are available on the microARCH github page
429 (@microARCHlab/BritishDentalCalculus_2021) as well as on
430 <https://github.com/michellepistner/ancientDNA>.

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447

448 **Author Contributions**

449 A.G.F., N.G., A.C., K.D., and L.S.W. conceived of the study and developed the experimental
450 design. A.C., A.G.F., C.A., K.B., K.D. and L.S.W. worked on sample acquisition. A.G.F.
451 completed the laboratory analysis. A.S.G., A.G.F., S.W. and L.A. completed the
452 bioinformatics and computational analysis. A.S.G., M.N., E.D., J.S., and L.S.W. performed
453 the statistical analysis. A.S.G., A.G.F., and L.S.W. wrote the manuscript, and all authors
454 edited and commented on the manuscript.

455

456 **Competing Interests**

457 The authors declare no competing interests.

458 **Figure Legends**

459

460 **Figure 1:** (A) Map showing the locations of the archaeological sites examined in this study
461 across the British Isles. Each site is represented by a circle, and the size of the circle
462 corresponds to the number of dental calculus samples examined from that site. A total of 235
463 individuals and 27 sites were sampled. (B) The number of dental calculus samples from each
464 time period is shown. The broad time periods and associated dates are: Pre-Roman Britain (–
465 43 CE), Roman Britain (43 CE – 410 CE), Anglo-Saxon/early medieval Britain (410 – 1066
466 CE), Norman Britain and the Middle Ages (1066 CE – 1547 CE), Reformation (1547 CE –
467 1750 CE), and Industrial (1750 CE – 1900 CE).

468

469 **Figure 2:** The contributions of oral geography on bacterial and archaeal taxonomic
470 compositions are displayed by performing a Principal Coordinates of Analysis (PCoA) of
471 Bray-Curtis distances for all teeth. The oral microbiota composition from each calculus
472 sample is colored according to (A) the tooth that was sampled; (B) the approximated size of
473 the dental calculus sample obtained for DNA extraction as described in the SI; or (C) the
474 surface of the tooth that was sampled shown for molar teeth only.

475

476 **Figure 3:** (A) A Principal Coordinates of Analysis (PCoA) plot displays differences in Bray-
477 Curtis distances of microbial genera present in each sample. Biplots are also displayed using
478 arrows for the top five most significant genera, with the length of the arrow proportional to its
479 magnitude. Samples are colored according to which the top three genera identified via
480 Biplots (*Actinomyces*, *Streptococcus*, or *Methanobrevibacter*) were most dominant within
481 each sample; samples that contained either more *Actinomyces*, *Streptococcus*, or
482 *Methanobrevibacter* are colored in grey, green, or pink, respectively. (B-C) CCLasso was
483 utilized to identify genera that positively (B) or negatively (C) cooccurred in all samples; the
484 top three genera identified using Biplots are colored as in (A): *Actinomyces*-associated (grey);
485 *Streptococcus*-associated (green), and *Methanobrevibacter*-associated (pink).

486

487 **Figure 4:** Normalized relative abundances of dietary microbial functions found to be
488 differentially abundant using a Benjamini-Hochberg corrected p value of a two-tailed
489 Welch's t test ($p < 0.05$) in ALDEx2 are displayed for *Streptococcus*-associated,
490 *Methanobrevibacter*-associated, and modern oral microbiomes. Red coloring represents high

491 abundances, yellow is medium, and while blue represents low; the coloring is normalized
492 within each dietary function category. A full list of functions tested is shown in Table S14,
493 and a full version of this differential abundance analysis is shown in Table S15.
494

495 **Table Legend**

496

497 **Table 1:** The results from ADONIS analysis on the beta diversity (Bray-Curtis) of oral
498 microbiota from all London individuals is shown in a table. The fit of the test (R^2) and the p-
499 value for each test are displayed for all species, genera, or all taxa present in each sample,
500 after accounting for oral geography. Significant results are highlighted in red ($p < 0.05$).
501 Results significant after implementing a Bonferroni correction are demarcated with *. Taxa
502 driving these shifts (Figure S19) and linkages to the dominant associated taxa (Table S23) are
503 presented in the Supplemental Text.

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Main Text Table: ADONIS of Culture and Health Variables For All Teeth and Molars, With Factors Based On Oral Geography Tables Accounted Into Models for MoL Samples Only

Variable (All Teeth)	SPECIES		GENERA		ALL TAXA	
	R2	Pr(>F)	R2	Pr(>F)	R2	Pr(>F)
Black Death (1346-1353)	0.042271	0.013	0.030313	0.048	0.025943	0.115
Civil War (Pre, Post, or During)	0.016108	0.135	0.011964	0.283	0.01031	0.342
Date (300 year intervals)	0.034836	0.048	0.024156	0.198	0.022078	0.221
Date (400 year intervals)	0.029446	0.013	0.016392	0.12	0.013127	0.203
Overall Pathology	0.006137	0.755	0.008607	0.449	0.004815	0.737
Blood Disorder	0.004924	0.874	0.006369	0.667	0.003584	0.875
Non Specific Periostitis	0.011312	0.376	0.008351	0.485	0.006533	0.55
Overall Vertebral Pathology	0.007189	0.668	0.006596	0.6	0.002856	0.936
Vertebral Pathology (Facets)	0.011992	0.398	0.011231	0.326	0.008289	0.482
Vertebral Pathology (Schmorls Nodes)	0.01889	0.163	0.014865	0.201	0.012520	0.248
Vertebral Anomaly	0.003516	0.975	0.00074	0.999	0.003231	0.928
Overall Joint Score	0.014469	0.339	0.013742	0.278	0.008986	0.476
Osteophitic Lipping (Joints)	0.016424	0.252	0.015658	0.2	0.013047	0.293
Porosity (Joint)	0.018879	0.2	0.016178	0.216	0.008034	0.561
Dental Abscess	0.007348	0.802	0.006688	0.831	0.008883	0.689
Caries	0.013519	0.365	0.010129	0.552	0.006764	0.742
Hypoplasia	0.016002	0.315	0.014795	0.32	0.012569	0.413
Periodontitis	0.007565	0.738	0.006348	0.791	0.003939	0.936
Class	0.050463	0.817	0.047845	0.842	ND	ND
Hospital	0.008254	0.583	0.006867	0.68	0.003706	0.89
Rank	0.024601	0.375	0.022691	0.419	0.013996	0.698
Religion	0.069326	0.37	0.065258	0.523	ND	ND
Empire	0.022583	0.161	0.024645	0.121	0.009261	0.296
Sex	0.012235	0.229	0.010149	0.346	0.007244	0.506
Cemetery	0.078145	0.066	0.06099	0.307	0.056177	0.38
Rural vs. Urban	0.015152	0.454	0.013429	0.55	0.008919	0.73
Medieval vs. Post Medieval	0.013773	0.126	0.013609	0.107	0.009232	0.233
Age	0.0334	0.14	0.040031	0.053	0.039874	0.074
Dominant Community	0.295798	0.001	0.278079	0.001	0.270359	0.001
	SPECIES		GENERA		ALL TAXA	

Variable (Molars)	R2	Pr(>F)	R2	Pr(>F)	R2	Pr(>F)
Black Death (1346-1353)	0.051076	0.141	0.034373	0.529	ND	ND
Civil War (Pre, Post, or During)	0.030608	0.245	0.025953	0.287	0.22388	0.33
Date (300 year intervals)	0.045842	0.356	0.040998	0.438	0.033105	0.646
Date (400 year intervals)	0.033868	0.137	0.027913	0.238	0.023156	0.329
Overall Pathology	0.036885	0.071	0.053478	0.119	0.047454	0.014
Blood Disorder	0.029438	0.135	0.04632	0.157	0.029031	0.121
Non Specific Periostitis*	0.073858	0.001	0.068745	0.04	0.066492	0.002
Overall Vertebral Pathology	0.032115	0.101	0.022347	0.595	0.027613	0.146
Vertebral Pathology (Facets)	0.017843	0.464	0.034455	0.369	0.011874	0.801
Vertebral Pathology (Schmorls Nodes)	0.020959	0.367	0.0136	0.908	0.017336	0.485
Vertebral Anomaly	0.007946	0.931	0.005958	0.998	0.012164	0.737
Overall Joint Score Osteophitic Lipping (Joints)	0.064592	0.007	0.100103	0.018	0.059902	0.012
Porosity (Joint)	0.064268	0.007	0.099268	0.022	0.060218	0.006
Dental Abscess	0.057578	0.014	0.099376	0.016	0.05229	0.022
Caries	0.034019	0.262	0.035143	0.531	0.036956	0.209
Hypoplasia	0.019593	0.573	0.031298	0.502	0.024434	0.334
Periodontitis	0.027694	0.268	0.036616	0.442	0.026032	0.291
Class	0.011512	0.833	0.025481	0.633	0.015703	0.026032
Hospital	ND	ND	ND	ND	ND	ND
Rank	0.023396	0.234	0.035948	0.274	0.026313	0.177
Religion	0.024147	0.82	ND	ND	0.022222	0.852
Empire	0.095904	0.117	ND	ND	0.093495	0.104
Sex	0.032085	0.089	0.026332	0.185	0.019894	0.321
Cemetery	0.0239	0.376	0.032519	0.187	0.023802	0.365
Medieval or Post Medieval	0.087245	0.159	0.088173	0.158	0.06858	0.385
Rural vs. Urban	0.030868	0.117	0.025388	0.169	0.019233	0.346
Age	0.033662	0.503	0.062878	0.296	0.037808	0.393
Dominant Community	0.049095	0.619	0.058474	0.37	0.047467	0.573
	0.221255	0.001	0.237476	0.001	0.187197	0.001

Bolding indicates a variable with significant results.

p<0.05

* Significantly associated with dominant category