



32 **Abstract**

33 The intestinal mucosa is at the front line of host-microbiome interactions, but little is known  
34 about these interactions within natural populations. Here, we non-invasively investigated  
35 associations between the gut microbiome and mucosal immune measures while controlling  
36 for host, social, and ecological factors in 199 samples of 158 wild spotted hyenas (*Crocuta*  
37 *crocuta*) in the Serengeti National Park, Tanzania. We profiled the microbiome composition,  
38 including bacteria, fungi and parasites, using a multi-amplicon approach, and measured  
39 faecal immunoglobulin A and mucin. Probabilistic models indicated that both immune  
40 measures predict microbiome similarity among individuals in an age-dependent manner. The  
41 strength of the association effect varied, being strongest within bacteria, intermediate within  
42 parasites, and weakest within fungi communities. Machine learning regression accurately  
43 predicted both measures and identified the taxa driving these associations: symbiotic  
44 bacteria reported in humans and laboratory mice, unclassified bacteria, a hookworm, host  
45 DNA likely reflecting inflammation, and diet. Our findings indicate a complex interplay  
46 between the host, its environment and symbionts. These findings increase our knowledge of  
47 the gut microbiome in natural populations, which harbour highly dynamic and diverse  
48 eukaryotes under the influence of unpredictable environmental factors and where selection  
49 is not artificially biased.

50

51 **Keywords**

52 gut microbiome; mucosal immunity; immunoglobulin A (IgA); mucin; natural population;  
53 spotted hyena; parasites; eukaryotes; bacteria; fungi; immune measures; non-invasive;  
54 wildlife

55

## 56 Introduction

57 The gut microbiome, the community of micro-and macroorganisms and their products or  
58 genetic material, residing within the gastrointestinal tract influences host physiology and  
59 plays a vital role in maintaining homeostasis and health <sup>1</sup>. In turn, the host's physiology,  
60 particularly the mucosal immune system, shapes this community. The intestinal mucosa, a  
61 single layer of epithelial cells covered by the mucus layer, is the first line of defence against  
62 pathogen translocation and fosters the maintenance of beneficial taxa <sup>2,3</sup>. It produces and  
63 releases a variety of enzymes and various immune defence molecules, e.g. antimicrobial  
64 peptides, mucins, and antibodies, to maintain intestinal homeostasis <sup>4-6</sup>. Perturbations of this  
65 community are associated with intestinal diseases, often accompanied by increased  
66 mucosal permeability and disrupted immune responses <sup>7-9</sup>.

67 Two important and broad-acting measures of mucosal immunity are secretory  
68 immunoglobulin A (IgA) and mucins. IgA is the primary antibody secreted into the intestinal  
69 lumen. It coats the surface of a broad but defined subset of gastrointestinal taxa <sup>10</sup> and is a  
70 substantial metabolic substrate for microorganisms <sup>11,3</sup>. IgA also prevents pathogens from  
71 crossing the intestinal epithelium and neutralises toxins and virulence factors <sup>12</sup>. All these  
72 processes selectively promote or hamper the colonisation and growth of specific taxa,  
73 thereby supporting the intestinal barrier in the control of the gut microbiome. Mucins form a  
74 mucus layer that covers the epithelium, serves as a lubricant to protect against mechanical  
75 stress, and limits its direct contact with toxins, digestive enzymes and potential pathogens  
76 <sup>13,14</sup>. Mucins are also important metabolic substrates for the gut microbiome, providing  
77 attachment sites that promote colonisation and provide a selective environment for  
78 symbionts <sup>15,14</sup>. Despite a growing body of knowledge of interactions between intestinal  
79 mucosal immunity and microbiome, the focus remains disproportionately on bacteria <sup>16,17</sup>.

80 Although bacteria outnumber eukaryotes within mammalian intestines <sup>18</sup>, eukaryotes such as  
81 fungi, helminths and protozoa also play a significant role in regulating the gut microbiome <sup>19</sup>

82 and host health<sup>20-22</sup>. Studies on immune responses to fungi and parasites (i.e. protozoans  
83 and helminths) are often performed in isolation from the rest of the intestinal community,  
84 although inter-species interactions likely shape both the gut microbiome and immune  
85 responses<sup>23-25</sup>. Host-microbiome interactions via mucosal immunity are poorly understood,  
86 and the knowledge gap is even wider in wild animal populations, where the acquisition of  
87 samples can be challenging and species-specific reagents and appropriate immune assay  
88 validations are limited<sup>26</sup>.

89 Wild animals living in natural environments have a distinct microbiome compared to their  
90 captive counterparts<sup>27</sup>, characterized by a higher diversity of eukaryotes<sup>28,29</sup>. The study of  
91 host-microbiome interactions in wild animals has provided important insights into how host  
92 characteristics and the ecological environment shape their intestinal communities.  
93 Microbiome composition changes with age and between life stages, particularly during  
94 ontogeny, as observed in several mammals<sup>30-32</sup>. This effect is often attributed to changes in  
95 host physiology, particularly immune development, but also behavioural and dietary  
96 changes. Additionally, the host environment (biotic and abiotic factors) shapes the  
97 composition of gut microbiomes, as seen by spatial and temporal heterogeneities<sup>33-35</sup>, the  
98 effect of diet<sup>36,37</sup> and social interactions<sup>38,39</sup>. Importantly, the environment interacts with host  
99 physiology and genetics, and these interactions might change over time and are as such  
100 context dependent<sup>40</sup>. Long-term individual-based field studies allow the collection of detailed  
101 data on the life histories of individually recognised animals and on the biotic and abiotic  
102 environment, often with minimal anthropogenic manipulation. These are particularly suitable  
103 to disentangle the relative contributions of host characteristics and ecological factors in  
104 shaping microbiome composition and potential interactions within this community and with  
105 the host<sup>41-43</sup>.

106 Here, we study a wild population of spotted hyenas (*Crocuta crocuta*) in the Serengeti  
107 National Park, monitored within a long-term research project, to investigate the links  
108 between intestinal mucosal immunity and gut microbiome. Spotted hyenas (hereafter

109 'hyenas') live in stable social groups (clans) with a linear dominance hierarchy (i.e. with  
110 social ranks) in which females and their offspring socially dominate immigrant males <sup>44,45</sup>.  
111 Because they both hunt and scavenge and thus can consume fresh and highly decomposed  
112 carcasses <sup>46</sup>, hyenas can be exposed to a variety of pathogens. Additionally, pathogen  
113 transmission among clan members is facilitated due to their high rate of social interactions  
114 <sup>47-49</sup>. Nonetheless hyenas are known to be able to remain healthy <sup>47,50</sup>, suggesting specific  
115 adaptations such as a specialised immune system and/or resilient intestinal community <sup>48,51</sup>.  
116 Previous research has shown that host characteristics (e.g. age) and environment (e.g. clan  
117 membership) affect parasite infections <sup>49,52,53</sup> and intestinal bacterial composition <sup>30,54,55</sup>.  
118 Furthermore, faecal IgA and mucin reflect *Ancylostoma* load, a parasite shown to reduce  
119 longevity in the Serengeti population <sup>49,56</sup>. We hypothesised that the host-associated taxa are  
120 under tight regulation by mucosal immunity and are thus strongly associated with faecal IgA  
121 and mucin levels.

122

## 123 **Materials and methods**

### 124 **Study site, population under study and sample collection**

125 We collected life-history, behavioural and ecological data, and 210 faecal samples from 165  
126 individually recognised wild spotted hyenas from 2004 to 2018, Figure 1A, Figure S1.  
127 Hyenas from this study belong to three clans monitored on a near daily basis since 1987,  
128 1989, and 1990 in the context of an ongoing long-term individual-based research project in  
129 the Serengeti National Park (SNP), Tanzania. Individuals are recognised based on their  
130 unique spot patterns and other features, such as scars and ear notches <sup>44,57</sup>.

131 Cubs were aged to an accuracy of  $\pm 7$  days based on their behaviour, movement  
132 coordination, size and pelage when seen for the first time <sup>58</sup>. By the age of approximately  
133 three months, sex was determined by the shape of the external genitalia, particularly the  
134 dimorphic glans morphology of the erect phallus <sup>59</sup>. Maternal identity was determined based

135 on nursing observations at the communal den(s) and was further confirmed by DNA  
136 microsatellite loci analysis<sup>60</sup>.

137 The social rank of adult females in their clans was determined based on the observation of  
138 submissive acts in dyadic interactions recorded *ad libitum* and during focal observations<sup>61</sup>.

139 For each clan, we used the outcome of these dyadic interactions to construct an adult  
140 female linear dominance hierarchy that was updated daily after demographic changes  
141 (recruitment or deaths of adult females) and socially mediated changes in rank (coups). To  
142 make rank positions comparable across clans and within clans when the number of females  
143 in the hierarchy changed, we assigned standardised ranks, evenly distributing social ranks  
144 from the highest (standardised rank: +1) to the lowest rank (standardised rank: -1) within a  
145 clan. Juveniles (individuals younger than two years) were assigned the same standardised  
146 ranks as the mothers raising them at the sampling date<sup>62</sup>. Six hyenas sampled before  
147 reaching adulthood were adopted or jointly raised by their genetic and surrogate mothers<sup>62</sup>.  
148 In these cases, we assigned the social rank of the surrogate mother or the average of the  
149 rank of the mothers in the case of joint-raising.

150 Faecal samples were immediately collected after defecation and refrigerated in cool packs in  
151 the field until transport to the field station where they were mechanically mixed and aliquots  
152 stored at -10°C until transport to storage at -80°C in Germany<sup>52</sup>. Aliquots for DNA extraction  
153 were stored in RNAlater (Sigma-Aldrich, St Louis, MO, USA).

#### 154 **Faecal immunological assays**

155 Faeces aliquots were lyophilised for 22 hours in a freeze-dryer (Epsilon1-4 LSCplus, Martin  
156 Christ GmbH, Osterode, Germany) followed by homogenisation with mortar and pestles.  
157 Faecal mucin (f-mucin) and faecal immunoglobulin A (f-IgA) assays, previously adapted and  
158 validated for application to spotted hyena faeces, were applied using the methods described  
159 in detail in<sup>56</sup> and details are found in the Supplements.

160 **DNA extraction**

161 We extracted genomic DNA from faeces using the NucleoSpin®Soil kit (Macherey-Nagel  
162 GmbH & Co. KG, Düren, Germany) under the manufacturer's protocol with the following  
163 modifications: we performed mechanical lysis of the sample in a Precellys®24 high-speed  
164 benchtop homogeniser (Bertin Technologies, Aix-en-Provence, France) with two disruption  
165 cycles at 6000 rpm for 30 s, with a 15 s delay between them. We eluted DNA in a 40 µL TE  
166 buffer. Quality and integrity of the DNA were later evaluated with a full-spectrum  
167 spectrophotometer (NanoDrop 2000c; Thermo Fisher Scientific, Waltham, MA USA). We  
168 used a Qubit® Fluorometer and the dsDNA BR (broad-range) Assay Kit (Thermo Fisher  
169 Scientific) to quantify the concentrations of double-stranded DNA. The DNA extracts were  
170 adjusted to a final concentration of 50 ng/µl with nuclease-free water (Carl-Roth GmbH + Co.  
171 KG), and stored at –80°C, until further use.

172 **Library preparation and sequencing**

173 We used faecal DNA preparations for multimarker amplification using the microfluidics PCR  
174 system Fluidigm Access Array 48 x 48 (Fluidigm, San Francisco, California, USA). We  
175 randomised sample order and amplified samples in parallel with non-template negative  
176 controls using a microfluidics PCR. This allowed the amplification of multiple fragments  
177 (amplicons) for different marker genes (primer pairs in additional supplementary file 1). We  
178 integrated PCR setup library preparation into the amplification procedure according to the  
179 protocol for Access Array Barcode Library for Illumina Sequencers (single direction indexing)  
180 as described by the manufacturer (Fluidigm, San Francisco, California, USA). The amplicons  
181 were quantified using the Qubit fluorometric quantification dsDNA High Sensitivity Kit  
182 (Thermo Fisher Scientific, Walham, USA) and pooled in equimolar concentrations. The final  
183 library was purified using Agencourt AMPure XP Reagent beads (Beckman Coulter Life  
184 Sciences, Krefeld, Germany). The quality and integrity of the library were confirmed using  
185 the Agilent 2200 TapeStation with D1000 ScreenTapes (Agilent Technologies, Santa Clara,  
186 California, USA). Sequences were generated at the Berlin Center for Genomics in

187 Biodiversity Research (BeGenDiv) on the Illumina MiSeq platform (Illumina, San Diego,  
188 California, USA) using v2 chemistry with 500 cycles. All sequences are accessible in  
189 BioProject PRJNA1134446 in the NCBI Short Read Archive (SRA).

190 **Identification and quality screening of the amplicon sequence variants (ASVs)**

191 All analyses were performed using R v 4.4.0 <sup>63</sup>. For the initial analysis we used the packages  
192 dada2 v. 4.3.1 <sup>64</sup> and MultiAmplicon v. 0.1.1 <sup>65</sup> to filter, sort, merge, denoise and remove  
193 chimaeras for each run separately and for each amplicon, and removed contaminants with  
194 decontam v. 1.21.0 <sup>66</sup> using “prevalence” and “frequency” methods (method = “combined”).  
195 We further removed amplicon sequence variants (ASVs) with less than 1% prevalence, less  
196 than 0.005% relative abundance <sup>67</sup> and samples with less than 100 reads. Each amplicon in  
197 the multi-amplicon datasets was individually filtered and then all products were collated into  
198 an “phyloseq” object with the function “merge\_phyloseq” from the package phyloseq v.  
199 1.45.0 <sup>68</sup>. This last step resulted in 199 samples.

200 **Taxonomic annotation of ASVs**

201 We used the RDP classifier <sup>69</sup> implemented within dada2 v. 1.29.0 package <sup>64</sup> to assign  
202 taxonomy to the resulting ASVs. Sequences targeting the 18S, 16S, 28S and ITS rRNA  
203 genes were classified against the SILVA 138.1 SSU Ref NR 99, the SILVA 138.1 LSU Ref  
204 NR 99 <sup>70</sup>, the UNITE <sup>71</sup> databases, respectively. We used the SILVA 138.1 SSU Ref NR 99  
205 to classify 18S and 16S rRNA gene sequences, the SILVA 138.1 LSU Ref NR 99 databases  
206 <sup>72</sup> for 28S rRNA gene sequences, and the UNITE database <sup>73</sup> for ITS rRNA gene sequences.  
207 All other sequences from targeted regions without publicly available curated databases were  
208 classified against sequences downloaded from NCBI using RESCRIPt <sup>74</sup>.

209 **Merging ASVs into combined ASV (cASV)**

210 Our final dataset had ASVs from different amplicons targeting different marker loci of the  
211 same taxon. Hence, we merged the ASVs originating from the same taxon on the basis of  
212 their co-abundance within each genus (n = 476). Co-abundance networks were constructed

213 based on positive (Pearson coefficient  $> 0$ ) and significant correlations ( $p < 0.01$ ), after  
214 correction for multiple testing with the Benjamini-Hochberg method. ASVs that clustered  
215 together using the “cluster\_fast\_greedy” function from the igraph package <sup>75</sup> were then  
216 merged into one ASV by summing their abundances into combined ASVs (cASV). This has  
217 been previously accessed for *Eimeria* spp. <sup>76</sup> and is now extended to all annotated genera.

218 **Statistical analysis**

219 We conducted all analyses using R 4.4.0 <sup>63</sup>. The intestinal community composition was  
220 decomposed into four groups of cASVs: 1) bacteria domain, including the phyla Firmicutes,  
221 Bacteroidota, Campylobacterota, Cyanobacteria, Proteobacteria, Planctomycetota,  
222 Fusobacteriota, Actinobacteriota, Deferribacterota, Spirochaetota, Desulfobacterota and  
223 unclassified (unknown) bacteria; 2) fungi, including the phyla Mucoromycota, Ascomycota,  
224 Basidiomycota, Blastocladiomycota, Chytridiomycota, Neocallimastigomycota; and 3)  
225 parasites, including the known protozoa and helminth genera *Sarcocystis*, *Spirurida*,  
226 *Rhabditida* (*Ancylostoma*), Diphyllobothriidea, Cyclophyllidea, *Cryptosporidium* and  
227 *Ascaririda*. We investigated the gut microbiome variation among samples by calculating the  
228 pairwise distances ( $\beta$ -diversity) based on the abundance (Bray-Curtis distances) of all  
229 identified cASVs. We used the package vegan v. 2.6-4 <sup>77</sup> with the function “distance”.  
230 Dissimilarity distances were then transposed to similarity distances (1-Bray-Curtis  
231 distances).

232 We tested the effect of individual repeatability on  $\beta$ -diversity measures in 78 samples from  
233 37 individuals in the overall microbiome and in restricted datasets of bacteria, fungi, and  
234 parasite members. We used distance-based intraclass correlation coefficients (dICC) and  
235 standard errors (SE) calculated based on 1000 bootstrap iterations, implemented with the  
236 package GUniFrac v.1.7 <sup>78</sup>.

237 We tested for the association of immune measures while accounting for the effects of other  
238 known or expected host, social, and ecological variables on the  $\beta$ -diversity of the intestinal

239 microbiome composition using dyadic comparisons (distances) among samples (excluding  
240 within-sample comparisons), as previously described <sup>39,79,80</sup>. Host variables included age  
241 distance in days (Figure 1B), distances in f-IgA (Figure 1C), f-mucin levels (Figure 1D) and  
242 genetic mother. The ecological and social environment variables included distances in the  
243 standardised social rank, clan (same or different) and temporal distances (the distance in  
244 sample collection in days). We included an interaction between age and f-IgA and between  
245 age and f-mucin based on previous findings <sup>56</sup>. We applied Bayesian generalised linear  
246 multilevel models using the Markov chain Monte Carlo algorithm No-U-Turn Sampler (NUTS)  
247 <sup>81</sup> implemented in Stan through the brms package v. 2.19.0 <sup>82</sup>. We used a multi-membership  
248 random-effects framework that accounts for individuals in each pairwise comparison (e.g.,  
249 Individual A, Individual B). All predictors were scaled to values ranging from 0 to 1 to allow  
250 comparison of the standardised estimates of the predictors. We used four Markov chains,  
251 with 4 chains, 3000 iterations and 1000 burn-in iterations (warmup) to calibrate the Sampler,  
252 and default uninformative priors. We visually inspected convergence and assessed the  
253 relevance of each predictor by analysing R-hat values and the 95% credible intervals (95%  
254 CI). R-hat values provide information about chain convergence - when below 1.01, they were  
255 accepted as indicators of good convergence. A parameter was considered "significant" when  
256 the 95% CI did not include zero.

257 We applied a multivariate model to each microbiome component (parasites, fungi and  
258 bacteria), with the same predictors as the previous model and further captured the  
259 correlation between each group. We repeated all models using both occurrence i.e.  
260 presence/absence (Jaccard distances) and an alternative abundance-based  $\beta$ -diversity  
261 measure (Aitchison distances), see Supplements, Table S1.

262 We applied a complementary method to further investigate the associations between  
263 immune measures (f-IgA and f-mucin) and overall microbiome composition. We  
264 implemented random forest regression, a tree-based ensemble machine learning in the  
265 package caret v. 6.0-94 <sup>83</sup>, and implemented the ranger method in the ranger package v.

266 0.15.1<sup>84</sup>. The dataset was divided into training (80% of the samples) and test (the remaining  
267 20%) sets using the function “createDataPartition”, that used stratified sampling to create the  
268 splits, ensuring a representative distribution of the respective immune measure between the  
269 sets. Training and tuning were performed with the function “trainControl” using 10-fold cross-  
270 validation which was repeated 10 times. The final values used for the model predicting f-IgA  
271 were mtry = 346, splitrule = variance min.node.size = 10, and for f-mucin were mtry = 188,  
272 splitrule = variance and min.node.size = 10. We then evaluated the predictions by using the  
273 resulting model to predict each immune measure in the test dataset and compare them with  
274 the observed values to calculate R<sup>2</sup> from the respective regression model and Spearman  
275 correlation. Taxa importance was assessed based on permutation importance. We applied  
276 partial dependence plots using the package pdp v. 0.8.1<sup>85</sup> to evaluate the marginal effects  
277 of the top 20 important taxa for the f-IgA and f-mucin predictions and visualise the direction  
278 and linearity of these associations (Supplements, Figures S2 and S3). Many taxa were not  
279 classified at phylum or even domain levels. Thus, we confirmed the taxonomy of these taxa  
280 for each immune measure by searching for the most similar nucleotide sequences using  
281 NCBI BLAST searches<sup>86</sup> and by inspecting the top hits (E-value, Table S3).

282 Co-abundance network analysis was used to infer potential ecologically relevant taxa  
283 associations. We filtered cASVs to 20% prevalence (143 cASVs remained) to reduce  
284 sparsity and ensure robustness. Co-abundance networks were created with SParse InversE  
285 Covariance estimation for Ecological Association Inference (SPEIC-EASI), with the package  
286 SpiecEasi<sup>87</sup> using the “mb” neighbourhood selection method. The optimal lambda coefficient  
287 for the network was 0.316. Network visualisation was done using the package igraph version  
288 1.3.1<sup>88</sup>.

289

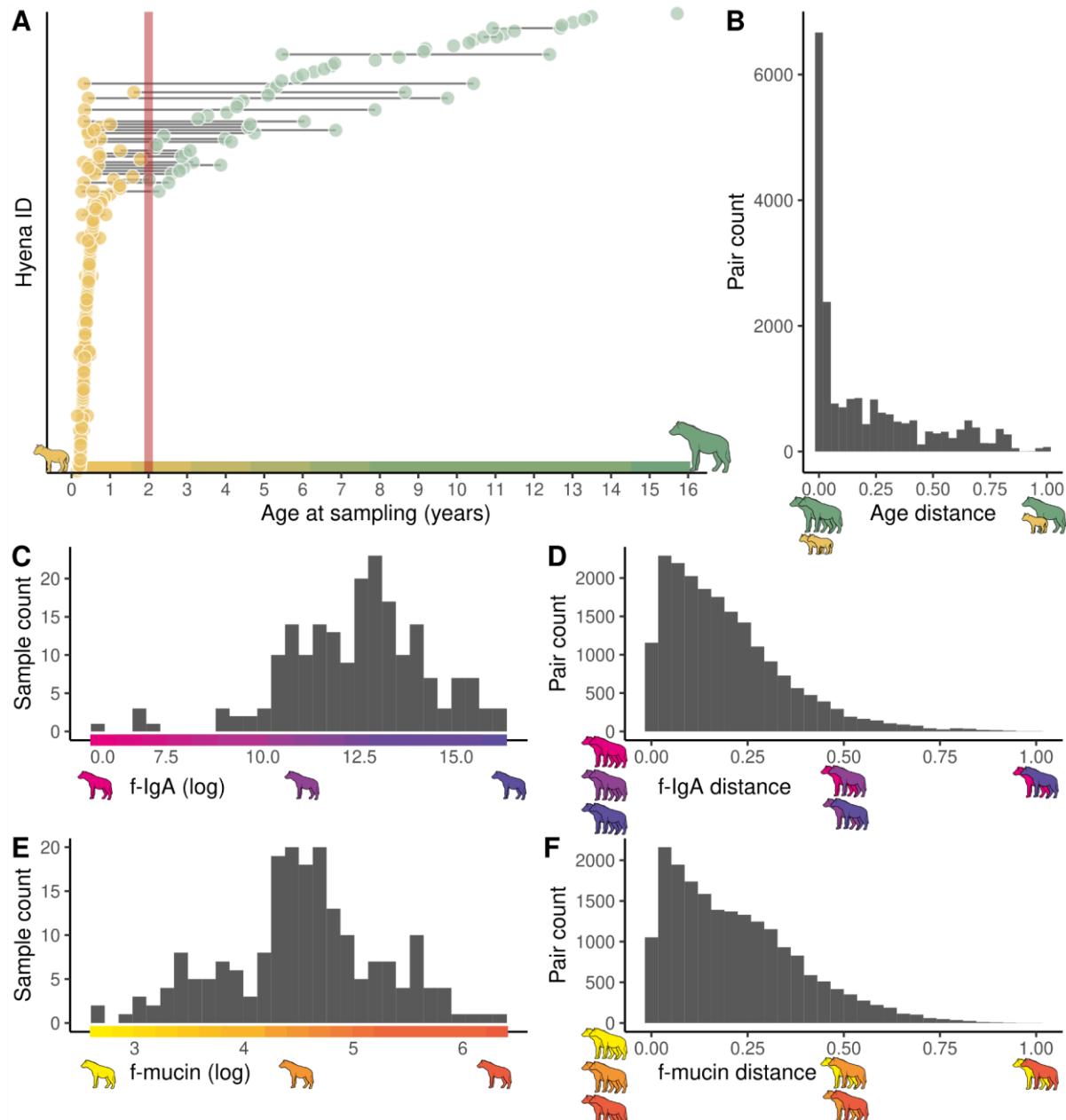
## 290 **Results**

### 291 **Intestinal communities of free-ranging hyenas**

292 We profiled the intestinal community of 158 free-ranging hyenas from three clans in the  
293 Serengeti National Park, sampled from 2004 to 2018. Thirty-seven individuals were sampled  
294 multiple times throughout their lives (Figure 1A). The median age of the animals at the time  
295 of sampling was 180 days, ranging from 52 days (1.7 months) to 5736 days (15.7 years). All  
296 adults were female (61 samples from 58 individuals) and juveniles were of both sexes (138  
297 samples from 41 males and 81 females).

298 The overall intestinal community was composed of 999 cASVs deduced from 3133 ASVs  
299 across 35 different amplicons. 301 cASVs originated from bacteria and 691 cASV from  
300 eukarya (Figure 2A-D). Out of the latter, we identified 420 cASVs as fungi and 25 cASVs as  
301 known eukaryotic parasites of spotted hyenas annotated as Rhabditida (*Ancylostoma*) (6  
302 cASVs), *Sarcocystis* (4 cASVs), *Spirurida* (3 cASVs), *Cystoisospora* (4 cASVs),  
303 *Cryptosporidium* (4 cASVs), *Ascaridida* (1 cASV), *Diphyllobothriidea* (1 cASV),  
304 *Cyclophyllidea* (2 cASVs). All but 5 samples had at least one parasite (cASV).

305 The repeatability within individuals tested multiple times was low or null for the overall  
306 intestinal microbiome (dICC = 0.084, SE = 0.037), bacteria (dICC = 0.061, SE = 0.049), fungi  
307 (dICC = -0.005, SE = 0.021), and highest for parasite composition (dICC = 0.108, SE =  
308 0.080).



309

310 **Figure 1.** Distributions of age and mucosal immune parameters in 199 samples from 158 free-ranging  
311 hyenas used in this study. **A)** Age at sampling. Samples from the same individual are connected with  
312 a grey line and dots are coloured based on the age category (yellow: juveniles, green: adults). The  
313 red vertical line indicates the age threshold between categories (2 years). **B)** Distribution of the age  
314 distance of compared samples. **C)** Distribution of faecal IgA. **D)** Distribution of faecal mucin. **E)**  
315 Distances between faecal IgA concentrations of all compared samples. **F)** Distances between faecal  
316 mucin concentrations of all compared samples. RU: relative units. Hyena icons are colour coded to  
317 illustrate the ranges of age and immune measures levels in the sampled individuals.

318

319 **Host immune measures are strongly associated with intestinal microbiome**

320 We found a strong effect of the faecal immune measures on the overall intestinal  
321 microbiome (Table 1). While controlling for genetic mother, social rank, clan membership,  
322 and temporal effects, animal-pairs with similar f-IgA or f-mucin levels show significantly more  
323 similar compositions of the overall microbiome than animals with different mucosal immune  
324 levels (Table 1, Figure 2E,F).

325

326 **Table 1.** The effects of host-related predictors (immune measures, age) and social and ecological  
327 environments on the overall and bacteria, fungi, or parasite-specific intestinal community composition  
328 similarity (Bray-Curtis similarity distance) based on Bayesian regression multi-membership models.  
329 We show the mean estimates of the posterior distribution for each predictor and the associated 95%  
330 credible intervals (CI). All predictors are expressed as distances between compared pairs (n=19701).  
331 Effect sizes in bold indicate significant predictors for which both upper and lower 95% credible  
332 intervals (CI) are either positive or negative.

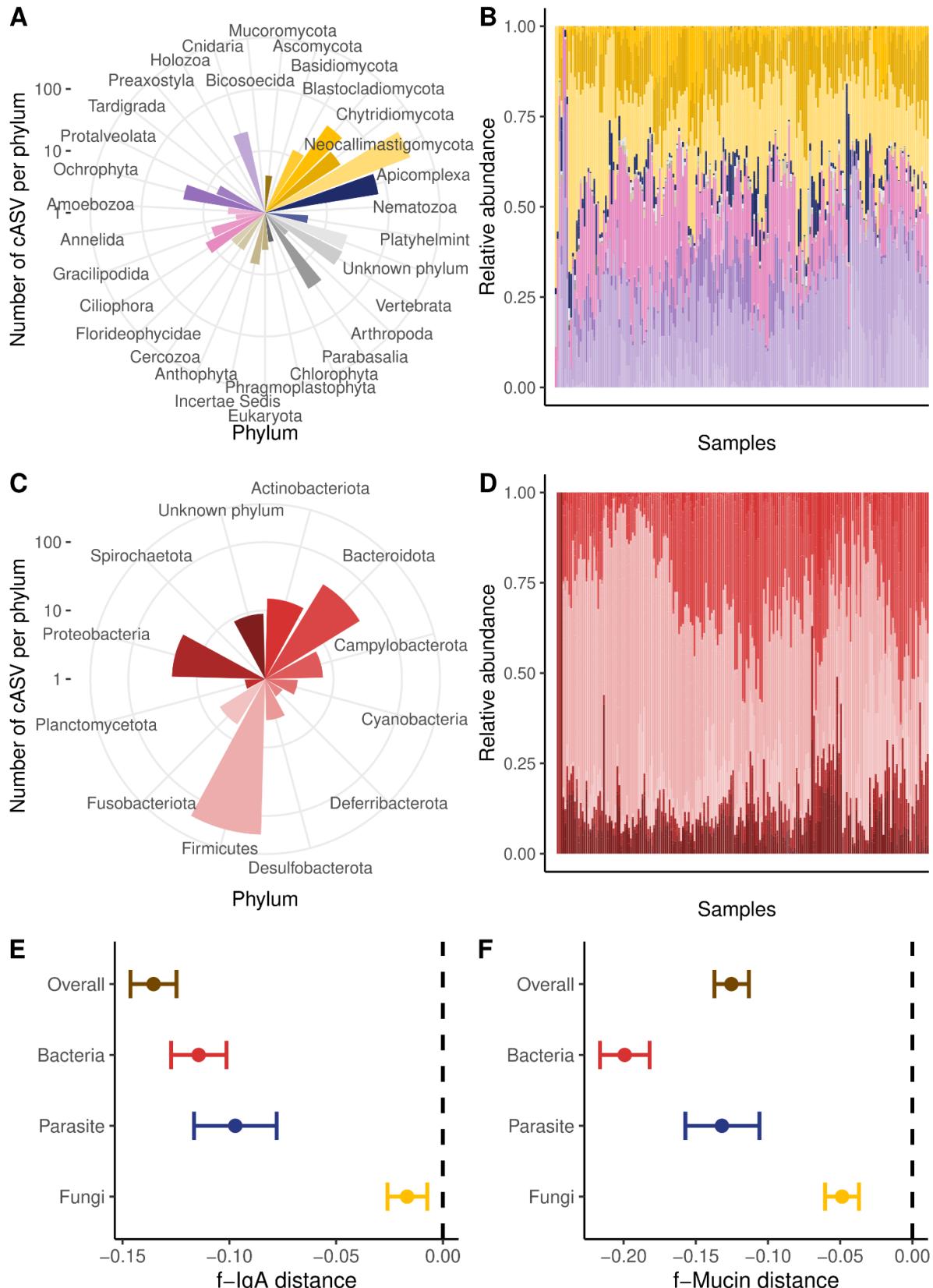
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| Predictors     | Overall                            | Bacteria                           | Fungi                              | Parasite                           |
|----------------|------------------------------------|------------------------------------|------------------------------------|------------------------------------|
|                | Estimate                           | Estimate                           | Estimate                           | Estimate                           |
|                | (credible interval)                | (credible interval)                | (credible interval)                | (credible interval)                |
| f-IgA dist     | <b>-0.060</b><br>(-0.072 – -0.048) | <b>-0.117</b><br>(-0.135 – -0.099) | <b>-0.013</b><br>(-0.025 – -0.001) | <b>-0.077</b><br>(-0.103 – -0.052) |
| f-mucin dist   | <b>-0.125</b><br>(-0.137 – -0.113) | <b>-0.199</b><br>(-0.216 – -0.182) | <b>-0.049</b><br>(-0.061 – -0.037) | <b>-0.132</b><br>(-0.157 – -0.106) |
| Age dist       | <b>-0.171</b><br>(-0.183 – -0.159) | <b>-0.195</b><br>(-0.212 – -0.177) | 0.004<br>(-0.009 – 0.016)          | <b>-0.154</b><br>(-0.180 – -0.127) |
| Social rank    | 0.002<br>(-0.003 – 0.007)          | 0.001<br>(-0.006 – 0.008)          | -0.001<br>(-0.006 – 0.004)         | 0.001<br>(-0.009 – 0.012)          |
| [same]         | 0.008                              | 0.009                              | 0.007                              | <b>0.026</b>                       |
| Genetic mother |                                    |                                    |                                    |                                    |

|                   |   |   |   |   |
|-------------------|---|---|---|---|
| [same]            | (-0.003 – 0.019)                          | (-0.007 – 0.025)                          | (-0.004 – 0.018)                          | <b>(0.002 – 0.050)</b>                    |
| Temporal dist     | <b>-0.012</b><br><b>(-0.017 – -0.006)</b> | <b>-0.012</b><br><b>(-0.020 – -0.004)</b> | <b>-0.032</b><br><b>(-0.038 – -0.027)</b> | <b>-0.018</b><br><b>(-0.029 – -0.006)</b> |
| Clan [same]       | 0.002<br>(-0.000 – 0.005)                 | 0.003<br>(-0.001 – 0.006)                 | -0.000<br>(-0.003 – 0.002)                | -0.003<br>(-0.008 – 0.002)                |
| f-IgA dist: Age   | <b>0.064</b>                              | -0.020                                    | <b>-0.046</b>                             | <b>0.115</b>                              |
| dist              | <b>(0.031 – 0.097)</b>                    | (-0.068 – 0.027)                          | <b>(-0.078 – -0.014)</b>                  | <b>(0.045 – 0.184)</b>                    |
| f-mucin dist: Age | <b>0.090</b>                              | -0.016                                    | <b>0.050</b>                              | <b>0.146</b>                              |
| dist              | <b>(0.059 – 0.121)</b>                    | (-0.061 – 0.030)                          | <b>(0.019 – 0.080)</b>                    | <b>(0.082 – 0.213)</b>                    |

335



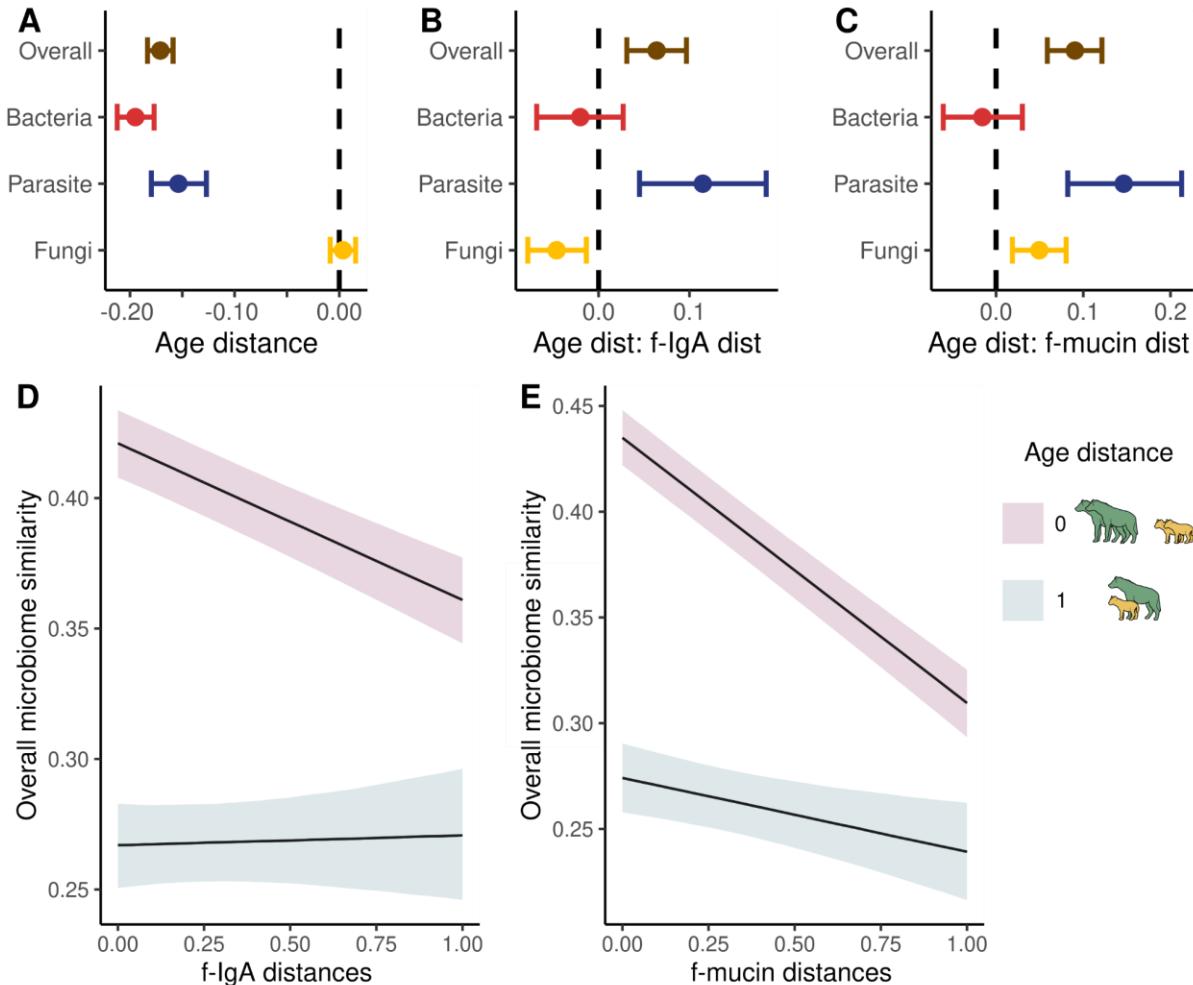
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337 **Figure 2.** The intestinal microbiome composition of 199 samples from 158 spotted hyenas. **A)** and **B)**  
 338 Eukaryote domain, **C)** and **D)** Bacterial domain. **A)** and **C)** depict the number of combined amplicon  
 339 sequence variants (cASV) per phylum, **B)** and **D)** represent the relative abundance of each cASV (y-

340 axis) for each sample (x-axis). Samples are sorted by clustering of Bray-Curtis dissimilarity. Colours  
341 represent the different phyla, with fungi in yellow, parasites in blue and bacteria in red. **E)** and **F)**  
342 Immune measures and age are strong predictors of intestinal microbiome composition. The  
343 compositional differences were analysed between samples using a Bayesian regression model with  
344 Bray-Curtis similarity estimates of  $\beta$ -diversity as independent variables. The figure shows the posterior  
345 distributions of the predictor variables: **E)** faecal IgA (f-IgA) level distances; **F)** faecal mucin (f-mucin)  
346 level distances. The overall model consists of the overall compositional differences among whole  
347 intestinal communities (999 combined amplicon sequence variants (cASVs), brown). The  
348 decomposed communities were further analysed: bacteria (301 cASVs, red), fungi (420 cASVs,  
349 yellow), and parasites (25 cASVs, blue). Dots represent mean effect sizes, and estimates and bars  
350 represent corresponding 95% credible interval (CI) on intestinal community composition similarity.  
351 Note that the ranges on the x-axis differ between the plots, reflecting different effect sizes.

352  
353 Age was the most important predictor of overall microbiome composition (Table 1). The  
354 similarity of the overall microbiome and the compositions of bacteria and parasites  
355 decreased with increasing age distances (Table 1, Figure 3A). The effects of immune  
356 measures depended on age for the overall microbiome, parasite, and fungi compositions  
357 (Table 1, Figure 3B-C). When pairs of samples from individuals of similar age were  
358 compared (purple lines in Figure 3D-E), the microbiome similarities (overall and parasite  
359 compositions) decreased with increasing f-IgA and f-mucin distances. When pairs with large  
360 age differences were compared (green-blue lines in Figure 3D-E), this effect became slightly  
361 less pronounced than in pairs with small age differences. On the contrary, fungi composition  
362 similarity became more pronounced with increasing f-IgA distances, but not f-mucin  
363 distances, than in pairs with small age differences (Figure 3B-C).

364



365

366 **Figure 3.** Similarity of the overall intestinal community composition is mediated by age. **A-C)** The  
367 compositional differences were analysed between samples using a Bayesian regression model with  
368 Bray-Curtis similarity estimates of  $\beta$ -diversity as independent variables. Age distances are important  
369 for all but the fungal members of the intestinal community. Shown are the posterior distributions of **A)**  
370 age, **B)** age interacting with f-IgA, and **C)** age interacting with f-mucin distances. The predicted  
371 similarity of the intestinal microbiome is displayed between sample pairs with similar animal age (age  
372 distance = 0) and in pairs with extreme age distances (age distance = 1) varying with **D)** f-IgA and **D)**  
373 f-mucin distances. The black lines indicate the mean predicted immune measures and the shaded  
374 area represent the 95% credible intervals (CI).

375

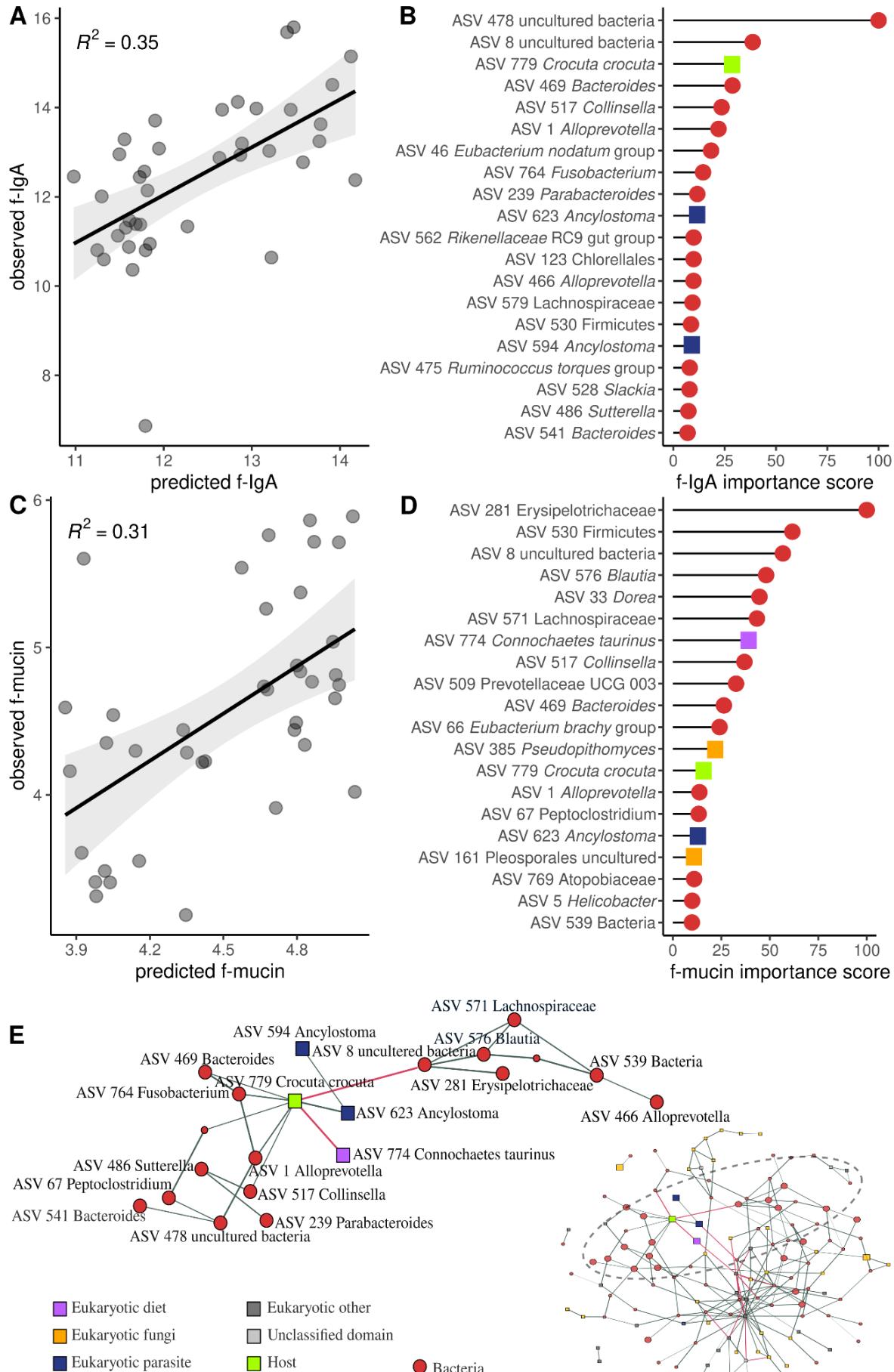
376 Temporal distances between the time of sampling, i.e. a large amount of time elapsed  
377 between the collection of two samples, decreased the microbiome similarity of the overall

378 microbiome composition and all microbiome members (Table 1). Sharing the same genetic  
379 mother had a small but significant positive effect on parasite composition similarity.

380 **Host immune measures are predicted by the overall intestinal microbiome  
381 composition**

382 To further investigate the association between the intestinal microbiome and mucosal  
383 immunity, we applied a random forest regression to the relative abundances of all 999 cASV  
384 identified to predict f-IgA and f-mucin. The 199 samples were divided into training (80%) and  
385 testing (20%) sets. Predicted and observed values correlated moderately for f-IgA ( $R^2 =$   
386 0.352, Spearman's rho = 0.599,  $p < 0.001$ ,  $n = 39$ , Figure 4A) and f-mucin ( $R^2 = 0.311$ ;  
387 Spearman's rho = 0.556,  $p < 0.001$ ,  $n = 39$ , Figure 4C). We identified the highest ranking  
388 cASVs (top 20 cASVs) according to the random forest importance score for predicting f-IgA  
389 (Figure 4B) and f-mucin levels (Figure 4D). Sequences are available in additional file 2.  
390 Partial dependence plots were used to visualise the marginal effects for each of the highest-  
391 ranking cASVs for predicting f-IgA (Figure S2) and f-mucin levels (Figure S3).

392 Among the highest-ranking predictors of f-IgA levels were 17 bacteria cASV, host DNA  
393 (cASV 776 *Crocuta crocuta*) and 2 parasite cASVs (both *Ancylostoma*). For f-mucin levels,  
394 the highest-ranking predictors were 15 bacteria cASVs, host DNA (cASV 779 *Crocuta*  
395 *crocuta*), prey DNA (cASV 774 *Chionochoetes taurinus*), one parasite cASV (cASV 623  
396 *Ancylostoma*) and two fungi cASV (cASV 385 *Pseudopithomyces* and cASV 161  
397 *Pleosporales* uncultured). Out of these, the same 7 cASV were predicting both f-IgA and f-  
398 mucin levels: cASV 8 (uncultured bacteria), cASV 779 *Crocuta crocuta*, cASV 469  
399 *Bacteroides*, cASV 517 *Collinsella*, cASV 1 *Alloprevotella*, and cASV 623 *Ancylostoma*.



401 **Figure 4.** Overall microbiome abundance predicts faecal IgA (f-IgA) and mucin (f-mucin) levels in  
402 hyenas. Random forest regressions were implemented with 999 combined amplicon sequence  
403 variants (cASVs) from 160 faecal samples (training set) and evaluated with an independent dataset of  
404 39 samples (test set), to predict **A**) and **B**) f-IgA levels and **C**) and **D**) f-mucin levels. The model  
405 accuracy was based on linear regression of predicted against observed **A**) f-IgA and **C**) f-mucin. Grey  
406 lines represent the regression lines from linear models calculated from the predicted against the  
407 observed respective immune measures, with the corresponding  $R^2$ . The top 20 most important cASVs  
408 for model prediction of **B**) f-IgA and **D**) f-mucin levels. Dots are colour coloured. Red represents taxa  
409 from the bacterial domain, blue parasites, yellow fungi, green host DNA, and lilac prey (diet) DNA. **E**)  
410 Co-occurrence network of 143 taxa across 199 samples from 158 spotted hyenas. Nodes represent a  
411 cASV and edges the association between a pair of cASVs. The edge thickness is scaled by  
412 association strength. The green and red edges represent positive and negative associations,  
413 respectively. The most important taxa for predicting both f-IgA and f-mucin are depicted in a larger  
414 node size. The area under the dashed ellipse is highlighted.

415

#### 416 **Inter-taxa associations**

417 Among compared animals, fungi composition similarity increased with parasite similarity  
418 (residual correlation estimate (CI) = 0.07 (0.06 - 0.09), and with bacteria similarity (residual  
419 correlation estimate = 0.12 (0.11 - 0.13) and bacteria similarity increased with parasite  
420 similarity (residual correlation estimate = 0.17 (0.16 - 0.19). We further investigated inter-  
421 taxa interactions with a co-abundance network of cASVs present in at least 20% of the  
422 samples. The resulting network contained 143 nodes and 219 edges (Figure 4E). The  
423 resulting network reflects a highly connected community, with the most important taxa for  
424 predicting both f-IgA and f-mucin being closely associated.

## 425 Discussion

426 The mammalian mucosal immunity and gut microbiome are in constant cross-talk. The  
427 resulting interactions are influenced by host characteristics and by the host's biotic and  
428 abiotic environments. Knowledge on symbiont-symbiont and symbiont-immune interactions  
429 is limited, especially outside the scope of human and model organism studies. Wild  
430 populations are exposed to and harbour a much more diverse array of macro- and  
431 microorganisms, live in heterogeneous environments and have diverse genetic  
432 backgrounds. Here, we explore the associations between two important and broad-acting  
433 measures of intestinal mucosal immunity, IgA and mucin, and the gut microbiome, while  
434 accounting for host characteristics, social rank, and environmental factors in Serengeti  
435 hyenas. Both IgA and mucin were strongly associated with the intestinal community and  
436 these associations varied in strength within different components of the gut microbiome,  
437 being stronger within bacteria, intermediate within parasites and weaker within fungi  
438 communities. The most important taxa predicting both immune measures were  
439 predominately bacteria and the parasite *Ancylostoma*. Our results link, for the first to our  
440 knowledge, mucosal immunity to intestinal microbiome composition, considering both  
441 bacteria and eukaryotes, in a wild population.

442 Bacteria had stronger associations with both IgA and mucin than parasites and fungi,  
443 regardless of host characteristics and the environment. Through a complementary analysis,  
444 we confirmed that the composition of the gut microbiome, particularly bacteria, predicted the  
445 levels of f-IgA and f-mucin well. This is not surprising, as bacteria outnumber eukaryotes in  
446 mammalian intestines <sup>89,28,90</sup> and in the metabolic products that are currently known to  
447 interact with the immune system <sup>91,92</sup>. Parasites were disproportionately associated with both  
448 immune measures, considering that they comprise fewer taxa than bacteria and fungi. This  
449 is expected, because parasites can tamper with immune responses to their own advantage,  
450 e.g. by secreting enzymes that degrade the mucin layer <sup>93</sup>. The association between fungi

451 and mucosal immunity is still poorly understood, but recent studies have revealed potentially  
452 relevant associations <sup>22,94</sup>.

453 Many of the identified predictive taxa are well-known intestinal symbionts in humans and  
454 mouse models, associated with either health benefits or detriments. Some of these bacterial  
455 taxa, including *Bacteroides*, *Alloprevotella*, *Peptoclostridium*, *Slackia*, and *Fusobacterium*,  
456 were previously identified as 'core gut symbionts', i.e. present in 85% of samples from a  
457 different population of spotted hyenas <sup>55</sup>. It is conceivable that these taxa provide relevant  
458 functions to hyenas. The *Bacteroides* genus is a common symbiont of humans <sup>95</sup> and other  
459 mammals <sup>96-98</sup> and its members have been associated with beneficial <sup>99</sup> and negative effects  
460 in their host <sup>100</sup>. Although the functional role in intestinal health is still largely unknown,  
461 *Alloprevotella* is suggested to have anti-inflammatory properties in humans <sup>101</sup>, is reduced  
462 after a stressful intervention in pigs (*Sus domesticus*) <sup>102</sup>, and is associated with the  
463 presence of helminths in wild chimpanzees (*Pan troglodytes*) <sup>103</sup>. Interestingly, two taxa from  
464 *Alloprevotella* abundance positively and negatively predicted f-IgA levels in our study, which  
465 might point to species or possibly strain-specific regulation by IgA in this genus. Taxa of the  
466 genus *Slackia* may exert an indirect anti-inflammatory effect in the gut via metabolite  
467 production that can maintain immunity homeostasis <sup>104</sup>. Taxa of the *Fusobacterium* genus  
468 are associated with disease states in humans and in its translational models. *F. nucleatum*  
469 causes inflammation by upregulating the activity of IgA in laboratory mice <sup>105,106</sup> and worsens  
470 colorectal cancer in humans <sup>107,108</sup>. Members of the genus *Peptoclostridium* can help  
471 maintain the intestinal barrier, among other functions <sup>109</sup>, but can also be life-threatening to  
472 humans and other animals <sup>110</sup>.

473 We found the parasite *Ancylostoma* to be positively associated with both f-IgA and f-mucin  
474 levels. *Ancylostoma* is a blood-feeding nematode that causes extensive inflammation and  
475 intestinal bleeding in several different species <sup>111-113</sup>. Our findings are consistent with those  
476 of a previous study in the same population, in which *Ancylostoma* egg load was found to be  
477 positively associated with both f-mucin and f-IgA <sup>56</sup>. We interpret this result as the potential

478 upregulation of IgA and mucin by the host in an unsuccessful attempt to eliminate adult  
479 *Ancylostoma* parasites from the gut. The presence of host DNA is also positively associated  
480 with f-IgA and f-mucin, which could indicate intestinal inflammation because of increased cell  
481 shedding leading to higher levels of host DNA in faeces <sup>114,115</sup>. In the co-occurrence network,  
482 host DNA is positively associated with both *Ancylostoma* and *Fusobacterium*, both of which  
483 are capable of causing extensive inflammation <sup>111–113,108</sup>. It is also possible that  
484 concentrations of IgA, mucin, and host DNA co-varied with intestinal transit or diet <sup>116,117</sup> and  
485 could be indicators of the host's normal variation through physiological states, although our  
486 results indicate that prey DNA is negatively correlated with host DNA, and host DNA  
487 correlated with a known parasite in hyenas, thus rather pointing to disruption or disease.

488 Our co-abundance network and inter-taxa correlations suggest a highly connected intestinal  
489 community. The taxa predicting f-IgA and f-mucin are closely associated, which potentially  
490 indicates a regulatory role of the mucosal immune system. Previous studies in wild non-  
491 human primates have also documented associations between parasites and bacteria, which  
492 are shaped by host-related and ecological factors <sup>118–120</sup>. The role and significance of fungi  
493 within the intestinal community remains to be elucidated given the scarcity of studies  
494 focusing on this taxonomic group within wildlife guts, but see <sup>35,118</sup>.

495 As expected from previous studies on hyenas <sup>30,56</sup> and other wild animals (e.g. wild primates  
496 <sup>121</sup>), we found that age is a strong predictor of microbiome similarity. Our results suggest that  
497 the strength of the associations between bacteria, parasites, and fungi on the one hand and  
498 mucosal immune measures on the other were modulated by host age. These effects were  
499 complex and inconsistent between measures of mucosal immunity and among the different  
500 components of the gut microbiome. The mammalian gastrointestinal tract is colonised at  
501 birth by pioneer microbes acquired from mothers and the environment <sup>122,123</sup> and the gut  
502 microbiome undergoes a process of microbial succession <sup>124</sup>. This process is closely linked  
503 to the maturation of the immune system, as the immune system requires microbial  
504 interactions early in life for proper development and maturation, and in turn shapes the

505 microbiome composition <sup>8,125</sup>. Our results are consistent with complex and context-specific  
506 interactions between the immune response and the host throughout life.

507 It is difficult to comment on the health effects of a particular microbiome community or even  
508 on those of individual taxon and associations, other than known parasites such as  
509 *Ancylostoma* <sup>56</sup>. Thus, we are cautious when interpreting the functional roles of individual  
510 taxa associated with mucosal immunity in this study. Different species, strains, and  
511 immunogenic potential within these taxa could lead to different outcomes in wild populations  
512 for which knowledge is still limited. Host-microbial interactions are context-dependent and  
513 are mostly studied in humans and laboratory translational models. In future studies,  
514 assessments of the effects of particular microbial communities on individual health (as  
515 measured using e.g. body condition) may help determine whether specific taxa are beneficial  
516 or not to hosts, and thus involved in shaping host evolutionary fitness. Because we  
517 measured broad-acting measures of mucosal immunity, we cannot infer specific  
518 mechanisms of interactions between the different members of the gut microbiome and the  
519 host. In the future, measuring antigen-specific IgA isoforms and mucin types together with  
520 assessments of intestinal communities may shed light on the finer details of the regulation of  
521 individual taxa in the biomes. In the broad absence of reagents for wildlife antibody detection  
522 <sup>126</sup>, IgA-seq, the enrichment of sequencing of IgA-coated taxa <sup>127,128</sup> could provide  
523 unprecedented insights into taxon-specific immune control at intestinal barriers. Investigating  
524 the link between host fitness, the microbiome and its metabolites could reveal evolutionary  
525 adaptations that promote or hamper host health and performance.

526 Natural populations harbour a hidden and mostly unknown diversity within their guts, and  
527 their immune systems must regulate such communities; maintaining mutualistic and  
528 commensals and reducing detrimental parasitic interactions. We identified broad and general  
529 associations between immune measures and the different members of the microbiome and  
530 pinpointed the taxa driving these associations. These findings indicate the important role that  
531 the immune system plays in the defence and also regulation of the microbiome, and we

532 propose that the identified taxa are closely associated with and involved in the cross-talk  
533 within the gut of natural populations of hyenas - a potential product of co-adaptation. The  
534 next step is to further investigate the genetic diversity and functional profiling of gut  
535 microbiomes in natural populations to uncover evolutionary aspects of such potential co-  
536 adaptations. We thus encourage others to approach wildlife microbiome research in a  
537 holistic manner and incorporate the measures of the immune system, both systemically and  
538 at mucosal sites, to improve our understanding of the complex and dynamic host-  
539 microbiome interactions.

540

## 541 **Author contribution**

542 EH, GAC, SB, AW, MLE and HH conceptualised the original study and acquired funding.  
543 SCMF, SPVS, EH and SB designed the analyses and computational framework. SCMF, SM,  
544 MLE, HH and SB conducted fieldwork. SCMF and MV performed the laboratory work for  
545 immune measures. VHJD and SK performed laboratory work for microbiome analyses.  
546 SCMF and EH analysed the data. SCMF and SPVS wrote the manuscript with contribution  
547 and feedback from SB and EH. All authors contributed significantly to editing the manuscript.

548

## 549 **Availability of data and materials**

550 The datasets supporting the conclusions of this article are available in the GitHub repository:  
551 [https://github.com/ferreira-scm/Microbiome\\_Hyena.git](https://github.com/ferreira-scm/Microbiome_Hyena.git). All sequencing raw data can be  
552 accessed through the BioProject PRJNA1134446 in the NCBI SRA.

553

## 554 **Funding**

555 We thank the Leibniz-Association for funding the EpiRank project (grant SAW-2018-IZW-3-  
556 EpiRank). We thank the Deutsche Forschungsgemeinschaft DFG (grants EA 5/3-1, KR  
557 4266/2-1, DFG-Grako 1121, 2046), the Leibniz Institute for Zoo and Wildlife Research, the

558 Fritz-Thyssen-Stiftung, the Stifterverband der deutschen Wissenschaft and the Max-Planck-  
559 Gesellschaft and Research Institute of Wildlife Ecology, University of Veterinary Medicine  
560 Vienna (SCMF) for financial support of the project. This work was also supported by the  
561 Deutsche Forschungsgemeinschaft (DFG) (Grant Number: 285969495/HE 7320/2–1), the  
562 German Academic Exchange Service (DAAD) (VHJD scholarship holder during PhD studies)  
563 and the Research Training Group 2046 “Parasite Infections: From Experimental Models to  
564 Natural Systems” (RTG-GRK2046: SS, MV and VHJD associated PhD student and EH, HH,  
565 MLE, GAC and SB as Senior Researchers).

566

## 567 **Acknowledgments**

568 For fieldwork, we were granted research permits from the Tanzania Commission for Science  
569 and Technology (COSTECH) and permission from the Tanzanian National Parks Authority  
570 (TANAPA) and Tanzanian Wildlife Research Institute (TAWIRI). Fieldwork was supported by  
571 the Commission for Science and Technology of Tanzania (COSTECH), the Tanzania Wildlife  
572 Research Institute (TAWIRI), and Tanzania National Parks (TANAPA). For laboratory  
573 support at the Leibniz Institute for Zoo and Wildlife Research (IZW), we thank D. Thierer, K.  
574 Pohle, F. Webster and C. Bost. We thank A. Francis, T. Shabani, M. Andris, N. Boyer, T.  
575 Golla, K. Goller, N. Gusset-Burgener, B. Kostka, M. Lindson, D. Thierer, A. Türk and K.  
576 Wilhelm for field and technical assistance.

577 All procedures and protocols were developed and implemented in compliance with the  
578 Leibniz Institute for Zoo and Wildlife Research Ethics Committee on Animal Welfare (permit  
579 number: 2017-11-02). Hyena icons were designed by Sonja Metzger.

580

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