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1 **Implementing network approaches to understand the socioecology of human-wildlife**
2 **interactions.**

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Abstract:

1. Human population expansion into nonhuman animals' habitats has increased interest in the behavioral ecology of human-wildlife interactions. To date, however, whether and how wild animals and their conspecifics form non-random associations in terms of when or where they interact with humans still remains unclear.
2. Here we adopt a comparative approach to address this gap, using social network analysis (SNA). SNA, increasingly implemented to determine human impact on wildlife spatial and social ecology, can be a powerful tool to understand how animal socioecology influences the spatiotemporal distribution of human-wildlife interactions.
3. For 10 groups of rhesus, long-tailed, and bonnet macaques (*Macaca* spp.) living in anthropogenically-impacted environments in Asia, we collected data on human-macaque interactions, animal demographics, and macaque-macaque agonistic and affiliative social interactions. We constructed 'human-interaction networks' based on associations between macaques that interacted with humans within the same time and spatial locations, and social networks based on macaque-macaque allogrooming behavior, affiliative behaviors of short duration (agonistic support, lip-smacking, silent bare-teeth displays, and non-sexual mounting), and proximity.
4. Pre-network permutation tests revealed that, for all macaque groups, human-interaction networks showed non-random structures. GLMMs revealed that individuals' connectedness within human-interaction networks were positively associated their connectedness within affiliation social networks, and social proximity networks although

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65 this effect varied across species (bonnets > rhesus > long-tailed). Male macaques were
66 more well-connected in human-interaction networks than females. Neither macaques'
67 connectedness within grooming social networks nor their dominance ranks had an
68 impact on human-interaction networks.

69 5. Our findings suggest that, in challenging, time-constraining anthropogenic
70 environments, less time-consuming affiliative behaviors and additionally greater social
71 tolerance (especially in less ecologically flexible species with a shorter history of
72 exposure to human activity) may be key to animals' maintaining strong social
73 connections. Subsets of these animals may also utilize greater exploratory tendencies
74 and life-histories that are less energetically demanding in the long-term. Both of these
75 strategies may contribute to animals' propensities to engage in joint risk-taking by being
76 near and engaging with humans. From conservation and public health perspectives,
77 human-interaction networks may inform interventions to mitigate zoonotic disease
78 transmission and move human-wildlife interactions from conflict towards co-existence.

79

80 **Key-words:**

81 Behavioral ecology

82 Comparative studies

83 Conservation behavior

84 Human-wildlife interactions

85 Nonhuman primates

86 Social Network Analysis

87

88 **Introduction:**

89 An expanding human population has increased overlap and contact rates between humans

90 and wildlife (Nyhus, 2016). The resulting human-wildlife interactions have visible, readily

91 discernible outcomes on wildlife populations, but also subtler effects on animal ecology and

92 behavior that remain less well-documented (Balasubramaniam et al., 2021). The sub-field of

93 conservation behavior addresses this gap, and largely deals with how anthropogenic factors

94 impact animal movement and (consequential) access to natural resources, interspecies ecosystem

95 interactions with predators and competitors, and intraspecies spatial overlap and social

96 interactions with their conspecifics (reviewed in Berger-Tal et al., 2016; Snijders et al., 2017).

97 However, there exists comparatively less research on the inverse effect – that is, on how animal

98 attributes that influence their life-history, or their interactions with socioecological components

99 of their natural environment, might impact their behavior in anthropogenic environments

100 (Balasubramaniam et al., 2021; Morrow et al., 2019). This is despite growing consensus that

101 human-wildlife interactions generate coupled, bi-directional effects whereby they both affect,

102 and are reciprocally affected by, wildlife ecology and behavior (Balasubramaniam et al., 2021;

103 Carter et al., 2014; Lischka et al., 2018).

104 More recently, however, a handful of empirical studies have focused on how the

105 socioecology of group-living wild animals can influence human-wildlife interactions.

106 Specifically, these have revealed how wild animals' tendencies to engage in risk-taking

107 behaviors within human-impacted environments are associated with a number of life-history and

108 socioecological traits, such as animals' sex, dominance rank, spatial position within their groups,

109 and connectedness within social networks (e.g. elephants, *Elephas maximus*: Chiyo et al., 2012;

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110 black bears, *Ursus americanus*: Lischka et al., 2018; multiple species of macaques, *Macaca* spp.:
111 Balasubramaniam et al., 2020a; Morrow et al., 2019). A common aspect of all these studies is
112 that they have focused on the overall frequencies of human-wildlife interactions, or the overall
113 degrees of exposure of individual wild animals to humans and anthropogenic factors. In
114 comparison, less well-studied is whether and how animals form non-random associations in
115 terms of when, where or how they interact with humans.

116 Understanding such patterns of associations in human-wildlife interactions is important
117 for many reasons. First, capturing the dynamic, spatiotemporally variant socioecology of human-
118 wildlife interactions could offer opportunities to study contemporary evolution, and animals'
119 propensities to adaptively respond to rapidly changing environments (Wong & Candolin, 2015).
120 Second, from a public health perspective, they could provide valuable information regarding
121 whether or how some animals, by virtue of overlapping with humans and anthropogenic areas
122 across time and space, may be the targets of interventions to mitigate the spread of zoonotic and
123 emerging infectious diseases at human-wildlife interfaces (Cunningham et al., 2017; Townsend
124 et al., 2020). Third, such animals may also be the targets of conservation efforts, interventions
125 and policy making aimed at decreasing human-wildlife conflict while increasing mutual welfare
126 and co-existence (Nyhus, 2016).

127 Network approaches offer exciting quantitative tools that may uniquely be able to address
128 this gap in the literature. Beyond just rates or durations of interaction, networks allow for
129 modeling the heterogeneity in relationships between entities (i.e. individual animals or humans;
130 assigned as nodes) based on shared or interactive patterns of their association (assigned as edges)
131 (Farine & Whitehead, 2015; Wey et al., 2008). In particular, social networks, which link animals
132 based on their shared patterns of space-use associations or contact and non-contact social

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133 interactions (Farine & Whitehead, 2015), have found wide-ranging applications in animal
134 behavioral ecology (Croft et al., 2008; Krause et al., 2014), including of late in conservation
135 behavior (Snijders et al., 2017). For instance, epidemiological studies have used animal social
136 networks to assess the vulnerability of wildlife populations to infectious disease outbreaks (Craft,
137 2015; Drewe & Perkins, 2015). More pertinently, an increasing number of studies have revealed
138 how interactions with humans may decrease the connectedness of animal social networks (e.g.
139 spotted hyenas, *Crocuta crocuta*: Belton et al., 2018; giraffes, *Giraffa camelopardalis*: Bond et
140 al., 2020; bottlenose dolphins, *Tursiops aduncus*: Chilvers & Corkeron, 2001; moor macaques,
141 *M. maura*: Morrow et al., 2019), and in extreme cases that involve the removal or relocation of
142 individual animals, to the fragmentation of social networks (e.g. Killer whales, *Orcinus orca*:
143 Williams & Lusseau, 2006). Such findings are of profound importance since decreased social
144 network connectedness or fragmentation can strongly impact animal health and reproductive
145 success (Nunn et al., 2015). Yet while most social network analysis has focused on space-use
146 overlap or social interaction networks, little research has implemented network approaches to
147 model human-wildlife interactions themselves, or even associations between wild animals that
148 co-inhabit anthropogenic environments at the same time and space (Sosa et al., 2021a).

149 One reason for this may be that researchers may face logistical and ethical challenges
150 while attempting to construct human-wildlife interaction networks. For instance, the inclusion of
151 humans or anthropogenic features as node(s) in human-wildlife ‘bimodal’ or ‘multimodal’
152 networks would require that researchers identify and track the behavior of individual people,
153 specific human sociodemographic communities, and/or other features of anthropogenic
154 landscapes that come into contact with wildlife (e.g. livestock, feral mammals: Bhattacharjee &
155 Bhadra, 2020). Collecting such data is not always feasible, in light of the considerable geospatial

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156 and sociocultural variation that researchers face while sampling human demographics,
157 experiences, and behavior (Barua et al., 2013; Dickman, 2010; Karanth et al., 2018). A more
158 feasible approach may be to record interactions between humans and pre-identified wild animals
159 across time and overlapping space, and ‘project’ these interspecies interactions into what are
160 effectively unimodal ‘social’ networks in which wild animals are linked based on their
161 interactions with shared features of their ecology (here, humans). Such projections have been
162 constructed before for other ecological networks, for instance the conversion of a primate-
163 parasite bimodal network into a unimodal ‘social’ network that linked nonhuman primate species
164 (nodes) based on the parasites they shared (edges) (Gomez et al., 2013). In the context of human-
165 wildlife interactions, such constructions would provide useful opportunities to determine whether
166 animals interact with humans in non-random ways across time and space, and the
167 socioecological determinants of such associations.

168 In this study, we implement a network approach to capture heterogeneity in associations
169 between humans and group-living wild nonhuman primates across time and space, for multiple
170 human-primate interfaces in Asia. We address the above gaps in our current understanding of the
171 ecology of human-wildlife interactions, by asking whether wild macaques (*Macaca* spp.) living
172 in human-impacted environments (1) associate in non-random ways based on when or where
173 they interact with humans, that are also (2) influenced by their demographic and behavioral
174 characteristics linked to their life-history and socioecology. Aside from sharing close
175 evolutionary histories with humans (Hasegawa et al., 1985; Roos & Zinner, 2018), wild primates
176 are also increasingly sharing ecological space and resource-use overlap with humans (Fuentes,
177 2012; Mckinney, 2015). Anthropogenic factors may present (in evolutionary time-scales)
178 relatively novel, socioecological constraints on wild primates, with individuals having to

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179 continuously adjust their behavior to adapt to human activities and behavior (Mckinney, 2015).
180 Among the most ecologically and behaviorally flexible of all nonhuman primates, many species
181 of macaque, particularly rhesus macaques (*M. mulatta*), long-tailed macaques (*M. fascicularis*),
182 and bonnet macaques (*M. radiata*), are considered ‘edge’ wildlife species that overlap and
183 experience spatiotemporally variant contact-rates and interactions with humans (Gumert, 2011;
184 Priston & McLennan, 2013; Radhakrishna & Sinha, 2011). At the same time, they also show
185 marked inter- and intra-specific variation in social interactions and (consequently) social network
186 connectedness with their conspecifics, which has been strongly linked to differences in their
187 evolutionary or phylogenetic relationships (Balasubramaniam et al., 2012; Thierry, 2007),
188 exposure to socioecological factors (Sterck et al, 1997), and exposure to anthropogenic impact
189 (Balasubramaniam et al., 2020b; Kaburu et al., 2019b; Marty et al., 2019). For these reasons,
190 they are well-suited model systems for implementing network approaches to understand
191 associations of human-wildlife interactions and their links to animal socioecology and behavior.

192 ‘Human-interaction networks’ were constructed for ten groups of three macaque species
193 living in anthropogenic environments. These networks linked individual, pre-identified
194 macaques based on their tendencies to interact with humans within the same time and space. To
195 determine whether macaques were associated in terms of their tendencies to interact with
196 humans in non-random ways across time and space, we first tested whether (p1) the patterning
197 and distribution of individuals’ connectedness within their human-interaction networks would be
198 significantly different from random. Second, we examined whether macaques’ human-
199 interaction networks were associated with their social networks. For this, we tested whether (p2)
200 the node centrality of individuals within their human-interaction networks was positively
201 associated with their centrality within their social grooming, proximity, and/or short-duration

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202 affiliation networks. We also explored the effects of individuals' sociodemographic factors, i.e.
203 their sex, dominance rank, and species, on their connectedness/centrality within their human-
204 interaction networks. As a cross-species comparison, we also determined whether the above-
205 predicted associations between human-interaction network centrality and social network
206 centrality varied across different macaque species.

207

208 **Materials and Methods:**

209 *Study sites and subjects:* Demographic and behavioral data were collected on ten groups
210 of macaques living in urban and peri-urban environments ranging from temperate areas in
211 Northern India, to tropical environments in Southern India and Malaysia. The groups were as
212 follows: four groups of rhesus macaques at a Hindu temple and the surrounding forested area
213 (three groups) and a town mall area (one group) in the city of Shimla in Northern India (31.05 N,
214 77.1 E); four groups of long-tailed macaques at a Hindu temple (two groups) and a recreational
215 park (two groups) in the outskirts of Kuala Lumpur in Malaysia (3.3 N, 101 E); and two groups
216 of bonnet macaques at a recreational area in the outskirts of the rural town of Thenmala within
217 the state of Kerala in Southern India (8.90 N, 77.10 E) (Balasubramaniam et al., 2020b; Marty et
218 al., 2020). Subjects were pre-identified, adult male and female macaques. At all three locations,
219 macaque home ranges overlapped with humans and anthropogenic landscape features. However,
220 there were systematic inter- and intraspecific differences in macaques' degrees of exposure to
221 humans, and indeed the frequency and types of interactions that they engaged/experienced with
222 humans, which informed our expectation of detecting both within- and between-site differences
223 or heterogeneity in human-interaction patterns. Supplementary Table 1 provides details on the
224 study groups and subjects of the study. More details regarding the similarities and differences

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225 between the study sites may be found in our previous publications (Balasubramaniam et al.,
226 2020b; Marty et al., 2020).

227 *Data collection:* Data were collected following a standardized protocol that was
228 implemented across all three field-sites, with inter-observer reliability being reached both within
229 and across sites (details in Kaburu et al., 2019a). All data were collected for five days a week,
230 between 9:00 am and 5:00 pm. Given the susceptibility of social network analysis to sampling
231 methods and sampling bias (Farine, 2017; Farine & Whitehead, 2015), particularly to the inter-
232 dependencies of data used to construct multiple types of networks, we used different sampling
233 approaches to collect data on human-macaque interactions and macaque-macaque social
234 behavior.

235 To record human-macaque interactions, we used an ‘event sampling’ approach (Altmann,
236 1974; Beisner & McCowan, 2013; Kaburu et al., 2019a). For each macaque group and site, we
237 divided their home-range that overlapped with anthropogenic settlements into a series of spatial
238 blocks of roughly equal sizes, within which human-macaque interactions were most likely to
239 occur (see Kaburu et al., 2019a for details). Choices of block numbers and locations differed
240 across groups, and were assigned during a preliminary ‘training’ phase (of ~2 months) during the
241 groups’ home-ranges were determined. However, block numbers and locations changed during
242 the course of data collection in accordance with any shifts we saw in macaques’ home ranges
243 that resulted in our adding or dropping event sampling at some blocks. Critically, block sizes
244 were uniformly similar within and across study sites, and were set such that observers could
245 potentially view and record all macaques and humans that were present within the block at a
246 given time. To record human-macaque interactions, observers visited these blocks in a pre-
247 determined, randomized order on each day. From a pre-assigned, fixed location within each

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248 block that maximized their visual field, observers recorded all human-macaque interactions that
249 involved pre-identified macaques that were present within the block for a ten-minute duration,
250 before moving on to the next block. We followed such a randomized block sampling approach to
251 avoid over-sampling of human-macaque interactions in more (versus less) densely populated
252 areas of macaques' home-ranges, which can result in sampling bias (Farine, 2017; Farine &
253 Whitehead, 2015).

254 A 'human-macaque interaction' was defined as any contact or non-contact behavior that
255 was initiated by a macaque towards a human (e.g. approach, aggression, begging for food), or by
256 a human towards a macaque (e.g. approach, aggression, provisioning with food), that elicited a
257 reaction behavior (e.g. submissive avoidance, fleeing, or screaming, counter-aggression,
258 acquiring and feeding on human foods) from the initial recipient. We defined an "event" as either
259 a single such interaction, or a series of such sequentially occurring interactions that were linked
260 to each other temporally and/or through common/multiple participants (more details and
261 definitions in Kaburu et al., 2019a).

262 'Focal animal sampling' (Altmann, 1974) was used to record macaque-macaque social
263 interactions and social proximity with conspecifics. On each day, and in each location, individual
264 macaques were followed in a pre-determined, randomized sequence for ten-minute durations. In
265 each session, we recorded events of dyadic agonistic interactions (aggressive and submissive
266 behaviors), social or allogrooming, and other forms of dyadic affiliation that were of shorter
267 durations than grooming (i.e. coalitionary support during social conflicts, lip-smacking, non-
268 sexual mounting, or silent bare-teeth displays in non-agonistic or peaceful contexts), that
269 involved the focal animal as either the initiator or the recipient. Once every two minutes within a
270 focal session, we temporarily ceased recording data in a continuous manner to conduct a point-

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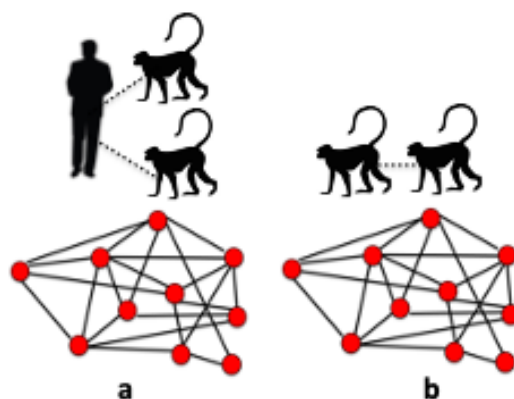
271 time scan of the focal, to record the identities of all group conspecifics that were within body-
272 length proximity of the focal. More details on the definitions of behaviors may be found in
273 Kaburu et al., 2019a.

274 *Construction of human-interaction networks and social networks:* For each macaque
275 group, undirected ‘human-interaction networks’ based on the spatiotemporal similarity of
276 monkeys’ interactions with humans (Fig. 1a) were constructed. That is, links between all
277 macaque subjects in a given group that engaged in human-macaque interactions within the same
278 ten-minute event sampling session and within the same block were assigned. Such
279 reconstructions enable determining whether macaques associated in non-random ways in terms
280 of their tendencies to interact with humans across time and anthropogenic space, and if so what
281 socioecological factors influence such associations. Edge-weights were calculated and assigned
282 to these human-interaction networks, as the ratio between the total number of such occasions in
283 which pairs of macaques spatiotemporally ‘co-interacted’ with humans, to the total duration of
284 event sampling sessions conducted during the course of their overlapping tenure within their
285 group, thereby accounting for their observability.

286 For each macaque group, we also constructed three types of weighted, undirected ‘social
287 contact networks’ based on our recordings of social macaque-macaque interactions of grooming,
288 short-duration affiliative behaviors, and social proximity (Fig. 1b). In grooming and short-
289 duration affiliation networks, nodes were individual macaques, and edge-weights were calculated
290 as the frequency of behaviors (given or received) between each pair of animals divided by the
291 total focal observation time of each member of that pair during the course of their overlapping
292 tenure within their group (details in Balasubramaniam et al., 2020a). In proximity networks,
293 edge-weights were calculated as the number of point-time samples in which a pair of individuals

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294 was seen within body-length of each other, divided by the total number of point-time samples
 295 collected for each member of the pair during the course of their overlapping tenure within their
 296 group.



297

298 **Figure 1: Macaque (a) human-interaction networks and (b) social networks**

299

300 *Calculations of dominance rank and social network centrality measures:* Using data on
 301 male-male and female-female dyadic aggressive interactions that elicited a submissive response
 302 from the recipient, we constructed dominance hierarchies separately for males and females for
 303 each group. Using these, we calculated the dominance rank of each macaque in each group,
 304 using the ‘Perc’ package in R (Fujii et al., 2015). To account for cross-group variation in group
 305 size, we standardized ordinal ranks to create a rank index ranging between zero (lowest-ranking
 306 macaque) and one (highest-ranking macaque) (Kaburu et al., 2019b). For each individual
 307 macaque within each type of network, we calculated weighted, undirected measures of their
 308 connectedness or centrality, both based on just their direct connections and by considering their
 309 secondary connections. First, we calculated *weighted degree* or (hereafter) *strength* as the sum of
 310 all the edge-weights of edges directly connected to an individual, i.e. the number and strength of
 311 an individuals’ direct connections (Croft et al., 2008; Newman, 2003). Second, we calculated

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312 *eigenvector* as the number and strength of an individuals' direct and secondary connections, i.e.
313 the reach of an individuals' connectedness or social ties (Bonacich, 2007; Brent, 2015).

314 There is broad consensus among behavioral ecologists that these centrality measures are
315 among the most biologically relevant (Sosa et al., 2021b). In the context of our human-
316 interaction networks, these measures would indicate the extent to which individual macaques
317 engaged with humans at the same time and space as others (strength). By taking into account
318 secondary connections, *eigenvector*, on the other hand, represents the extent to which individuals
319 interacted more with humans alongside group members who themselves interacted more with
320 humans while alongside other monkeys within the same time and space. In other words, we
321 anticipate that these measures of their connectedness would be relevant to understanding (i) the
322 socioecological underpinnings of macaques' risk-taking behaviors in anthropogenic
323 environments, and (ii) whether some individuals, due to their greater connectedness in one or
324 both types of networks, may serve as targets for interventions to manage human-wildlife
325 interactions and the risk of zoonotic transmission. To account for differences in group size (and
326 hence the number of nodes or available partners within a network), we re-scaled the values
327 calculated for each network measure within each group to sum up to one. Centrality measures
328 were calculated using the 'Igraph' package in R (Csardi & Nepusz, 2006).

329 *Data analysis:* To determine whether human-interaction networks showed non-random
330 structures (p1), we implemented a 'null' model pre-network randomization procedure (Farine,
331 2017; Farine & Carter, 2020). For each human-interaction network, we calculated the mean
332 strength centrality of all individuals, and compared this 'observed' mean to a distribution of
333 mean strength centrality scores calculated from each of 1000 permutations of the network
334 generated by randomly swapping its edges. This approach has been shown to be more reliable

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335 than other, post-network permutation-based null model approaches, i.e. node-swapping, to test
336 the ‘null’ hypothesis of random network structure (Puga-Gonzalez et al., 2020).
337 To test whether the structure of macaques’ connectedness within their human-interaction
338 networks were associated with their connectedness within social networks (p2), we ran General
339 Linear Mixed-effects Models (GLMMs) implementing a corrected Akaike Information Criterion
340 (AICc) based model-selection and interpretation approach, using the ‘Lme4’ R package
341 (Burnham & Anderson, 2002; Burnham et al., 2011).

342 For a sample size of 339 macaques across ten groups, we ran two sets of negative-
343 binomial models, one for each of two outcome variables of macaques’ human-interaction
344 network centrality measures, i.e. strength and eigenvector (Supplementary Tables 2 and 3). Each
345 model-set consisted of seven models. In each model set, the first model included only
346 sociodemographic attributes (i.e. sex, dominance rank, species) and was effectively the ‘null’ or
347 ‘control’ model. Models 2 and 3 included sociodemographic attributes plus a single measure of
348 macaques’ corresponding centrality (e.g. strength centrality as a predictor of human-interaction
349 strength centrality) in the grooming, short-duration affiliation, and proximity networks.
350 Centrality measures from the grooming and proximity networks (but not short-duration
351 affiliation networks) were strongly collinear and were not included in the same model. Finally,
352 models 4 to 7 included interaction terms between species and each social network centrality
353 measure to explore cross-species differences in associations.

354 From each model set, we shortlisted and interpreted model summary parameters from one
355 or more ‘candidate’ models that had the lowest AICc scores that were within an AICc of 2 points
356 from each other, and < 2 points from the next best-fit model. To account for inter-dependencies
357 in human-interaction network measures examined as outcome variables, we re-calculated the p

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358 values for the observed model coefficients for predictor variables that showed significant effects
359 in each candidate model, using a post-network node-swapping randomization procedure (Farine,
360 2017; Farine & Carter, 2020). In these, we compared observed model coefficients to a
361 distribution of coefficients generated by re-running the candidate GLMM following the re-
362 assignment of human-interaction centrality scores through randomly swapping the nodes of each
363 human-interaction network. Node-swapping is less susceptible (than pre-network randomizations
364 or edge-swapping) to type-II errors while testing regression-based null hypotheses (Weiss et al.,
365 2020).

366 We conducted various diagnostics of model validity and stability (Cook's distance,
367 dfBetas, and Variance Inflation Factors; distribution of residuals, residuals plotted against fitted
368 values) for all candidate models. These revealed no influential cases, strong collinearity among
369 our predictor variables, or obvious deviations from the assumptions of normality and
370 homogeneity of residuals (Quinn & Keough, 2002). All statistical tests were two-tailed, and we
371 set the p values to attain statistical significance to be < 0.05 .

372

373 **Results:**

374 *(P1) The structure of human-interaction networks:*

375 For all ten macaque groups, human-interaction networks were well-connected and
376 exhibited significant structure (examples in Fig. 2a-c). Table 1 summarizes the attributes and
377 characteristics of each network. The majority of human-interaction networks (7/10) were
378 somewhat fragmented, insofar as they had one or up to a few individuals that remained
379 disconnected from the main network fragment (a minimum of one individual in a bonnet
380 macaque group: BM_G2; a maximum of 7 individuals in a rhesus macaque group: RM_G4).

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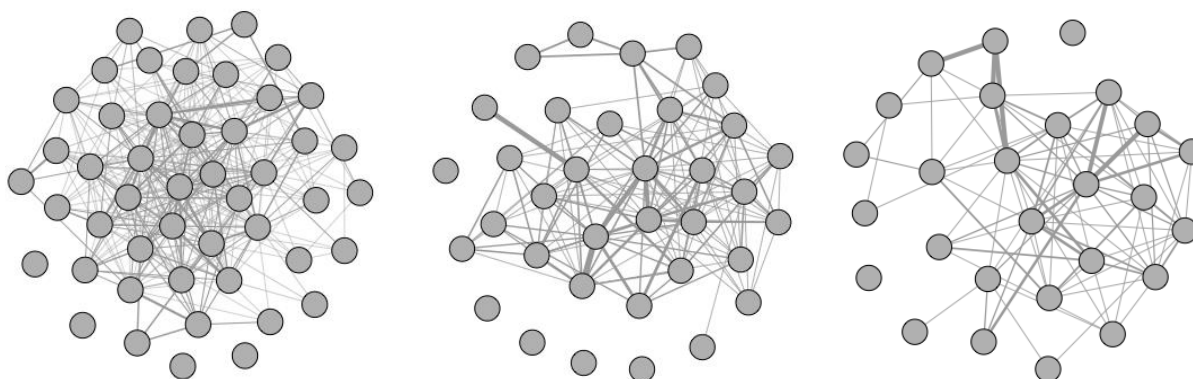
381 There was also marked inter-network variation in the average human-interaction strength
 382 centrality of individuals (Table 1). Despite these features, pre-network randomization tests
 383 performed by randomly swapping network edges revealed that, for each network, the observed
 384 mean strength centrality of individuals was significantly greater than the distribution of strength
 385 centralities calculated following 1000 permuted ‘edge-swapped’ networks. That is, all networks
 386 deviated significantly from the null hypothesis of random network structure.

387

388 **Table 1: Summary of attributes of macaque human-interaction networks. For mean**
 389 **strength, p values are based on a pre-network randomization procedure (see Methods)**

Species (group)	Network (group) Size	Males	Females	Edges or links	Unconnected individuals	Strength (mean \pm sd)
Bonnet (BM_G1)	48	26	22	318	4	0.10 \pm 0.07**
Bonnet (BM_G2)	28	10	18	115	1	0.09 \pm 0.06**
Long-tailed (LM_G1)	35	11	24	144	5	0.10 \pm 0.08**
Long-tailed (LM_G2)	19	7	12	122	0	0.30 \pm 0.16**
Long-tailed (LM_G3)	34	15	19	91	6	0.20 \pm 0.24**
Long-tailed (LM_G4)	24	5	19	178	0	0.23 \pm 0.14**
Rhesus (RM_G1)	27	9	18	87	2	0.08 \pm 0.06**
Rhesus (RM_G2)	24	7	17	173	0	0.10 \pm 0.05**
Rhesus (RM_G3)	41	13	28	342	2	0.05 \pm 0.03**
Rhesus (RM_G4)	59	14	45	238	7	0.05 \pm 0.03**

390 **p < 0.01



391

392 (a)

(b)

(c)

393 **Figure 2: Examples of weighted, undirected human-interaction networks constructed for**
 394 **groups of (a) bonnet macaques (BM_G1), (b) long-tailed macaques (LM_G1), and (c)**
 395 **rhesus macaques (RM_G1).**

396

397 *(P2) Associations between macaques' human-interaction networks and social networks:*

398 We found strong evidence to suggest that the connectedness/centrality of individual
 399 macaques within their social networks strongly influenced their connectedness/centrality within
 400 their human-interaction networks.

401 For strength centrality, our AICc selection criterion led to the short-listing and
 402 interpretation of two candidate GLMMs. The first candidate model (Table 2A: model 3 of
 403 Supplementary Table 2) showed a significant positive effect of both short-duration affiliation
 404 strength centrality (Fig. 3a) and proximity strength centrality on human-interaction strength
 405 centrality. The second candidate model (Table 2B: model 6 of Supplementary Table 2) further
 406 showed a significant interaction between proximity strength centrality and species, which
 407 revealed that the effect of proximity was most pronounced among bonnet macaques, moderate
 408 among rhesus macaques, and least pronounced (did not reach significance) among long-tailed

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409 macaques. Neither candidate model included grooming centrality measures: proximity and short-
 410 duration affiliation strength centrality had a greater impact than grooming strength centrality on
 411 human-interaction network centrality. Macaque sex had a significant impact on human-
 412 interaction network strength centrality, with males showing greater values than females (Table
 413 2A, B; Fig. 3b). However, dominance rank had no effect (Table 2A, B). Across species, we
 414 found that the average strength centrality of individuals was the highest among long-tailed
 415 macaques, and the lowest among rhesus macaques, with bonnet macaques falling in between
 416 (Table 2A).

417
 418 **Table 2: Candidate GLMMs (models 3 and 6 of Supplementary Table 2) examining the**
 419 **effects of individuals' sociodemographic attributes (sex, dominance rank, species), and**
 420 **social network strength centrality (grooming, proximity, and affiliation) by species, on their**
 421 **human-interaction network strength centrality. P_{perm} indicate p values from permuted**
 422 **networks that were estimated using the post-network randomizations or 'node-swapping'**
 423 **algorithm (see Methods).**

424 Model 3

Predictor	B	SE	Z	P	P_{perm}
(Intercept)	1.74	0.19	9.21	<0.01**	
Sex (males vs females)	0.30	0.11	2.67	0.01*	<0.01**
Rank Index	-0.10	0.17	-0.61	0.54	
Species (long-tailed vs bonnet)	0.57	0.19	2.98	<0.01**	<0.01**
Species (rhesus vs bonnet)	-0.35	0.19	-1.88	0.06(*)	
Species (long-tailed vs rhesus)	0.92	0.16	5.78	<0.01**	<0.01**

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Proximity Strength	8.30	3.35	2.47	<0.01**	0.03*
Affiliation Strength	7.34	2.81	2.61	<0.01**	<0.01**

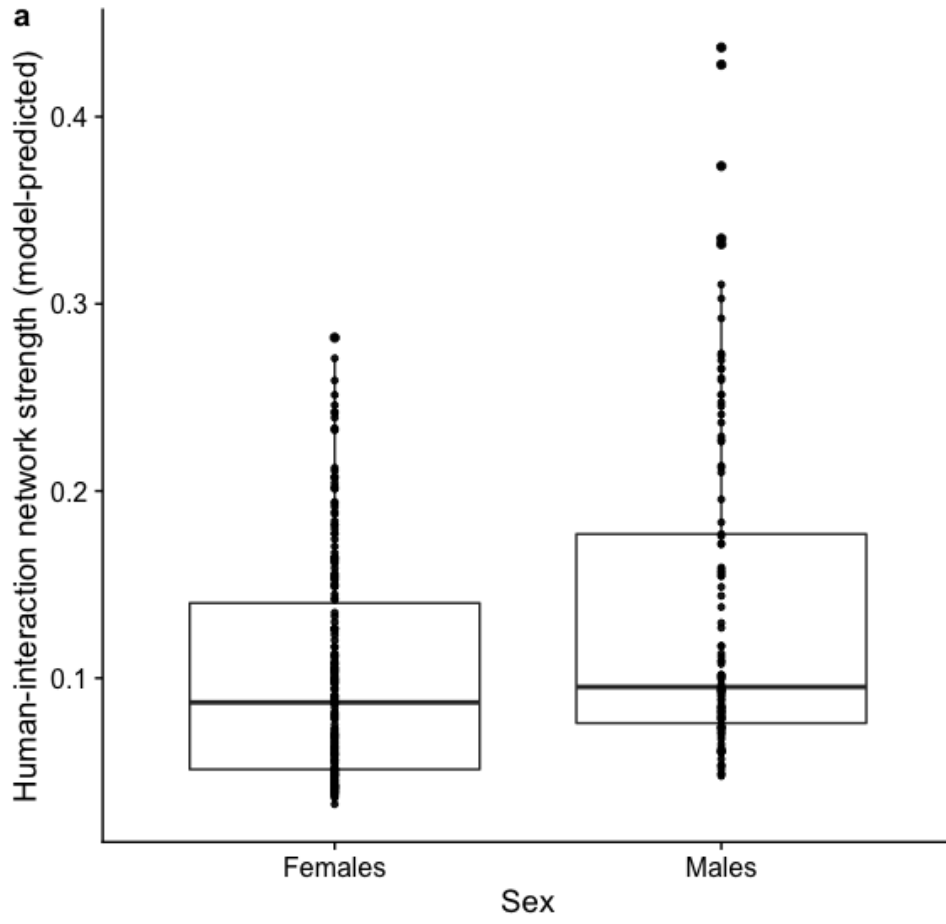
425 **p < 0.01; *p < 0.05; (*)0.05 < p < 0.10

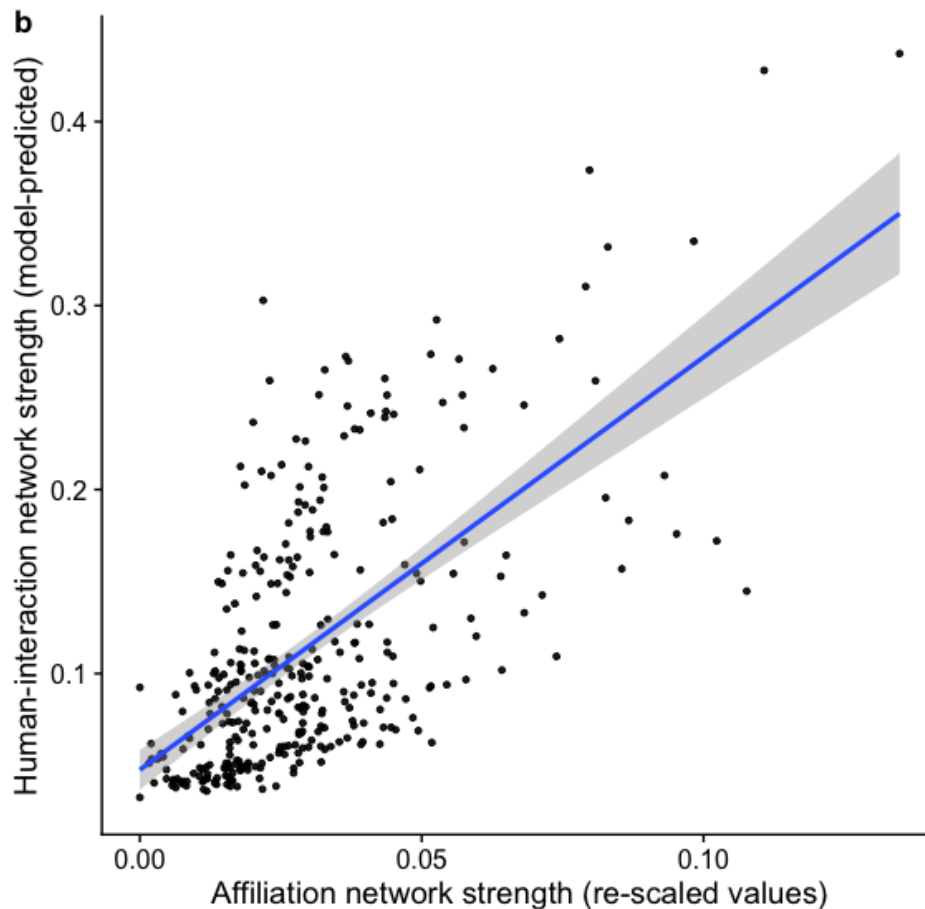
426 Model 6

Predictor	B	SE	Z	P	P_{perm}
(Intercept)	1.20	0.33	3.61	<0.01**	
Sex (males vs females)	0.40	0.12	3.42	<0.01**	<0.01**
Rank Index	-0.07	0.16	-0.43	0.67	
Species (long-tailed vs bonnet)	1.30	0.37	3.51	<0.01**	<0.01**
Species (rhesus vs bonnet)	-0.01	0.37	-0.04	0.97	
Species (long-tailed vs rhesus)	1.32	0.27	4.92	<0.01**	<0.01**
Affiliation strength	4.59	2.94	1.57	0.12	
Proximity strength (bonnets)	27.71	9.74	2.85	<0.01**	<0.01**
Proximity strength (long-tailed)	4.14	3.64	1.14	0.25	0.18
Proximity strength (rhesus)	16.48	5.85	2.82	<0.01**	<0.01**
Proximity strength (long-tailed vs bonnets)	-23.56	9.97	-2.36	0.02*	<0.01**
Proximity strength (rhesus vs bonnets)	-11.22	10.45	-1.07	0.28	
Proximity strength (long-tailed vs rhesus)	-12.34	6.28	-1.96	0.04*	0.04*

427 **p < 0.01; *p < 0.05

428





430

431 **Figure 3: Effect of (a) sex and (b) affiliation strength centrality on the outcome of human-**
 432 **interaction network strength centrality**

433

434 For eigenvector centrality, results were largely consistent. The first candidate model
 435 (Table 3A: model 3 of Supplementary Table 3) showed a significant positive effect of both short-
 436 duration affiliation eigenvector centrality (Fig. 4a) and proximity eigenvector centrality on
 437 human-interaction eigenvector centrality. The second candidate model (Table 3B: model 6 of
 438 Supplementary Table 3) further showed a significant interaction between proximity eigenvector
 439 centrality and species, which revealed that the effect of proximity was the strongest among
 440 bonnet macaques, moderately strong among rhesus macaques, and least strong (did not reach

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441 significance) among long-tailed macaques (Fig. 4b). Neither candidate model included grooming
 442 centrality measures, i.e. proximity and short-duration affiliation network centrality had a stronger
 443 (compared to grooming network centrality) impact on human-interaction network centrality.
 444 Macaque sex, but not dominance rank, had a significant impact on human-interaction network
 445 eigenvector centrality, with males showing greater values than females (Table 3A, B). However,
 446 unlike for strength centrality, there were no cross-species differences in mean human-interaction
 447 eigenvector centrality measures (Table 3A).

448

449 **Table 3: Candidate GLMMs (models 3 and 6 of Supplementary Table 3) examining the**
 450 **effects of individuals' sociodemographic attributes (sex, dominance rank, species), and**
 451 **social network eigenvector centrality (grooming, proximity, and affiliation) by species, on**
 452 **their human-interaction network eigenvector centrality. P_{perm} indicate p values from**
 453 **permuted networks that were estimated using the post-network randomizations or 'node-**
 454 **swapping' algorithm (see Methods).**

455 Model 3

Predictor	B	SE	Z	P	P_{perm}
(Intercept)	2.12	0.14	14.77	<0.01**	
Sex (males vs females)	0.18	0.11	1.61	0.01*	0.02*
Rank Index	-0.06	0.18	-0.33	0.74	
Species (long-tailed vs bonnet)	-0.07	0.13	-0.53	0.60	
Species (rhesus vs bonnet)	0.01	0.12	0.05	0.96	
Species (long-tailed vs rhesus)	-0.07	0.11	-0.67	0.50	
Proximity eigenvector	7.81	2.87	2.72	0.01*	0.01*

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Affiliation eigenvector	6.94	2.58	2.69	0.01*	0.03*
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456 **p < 0.01; *p < 0.05

457 Model 6

Predictor	B	SE	Z	P	P_{perm}
(Intercept)	1.71	0.25	6.93	<0.01**	
Sex (males vs females)	0.27	0.12	2.24	0.03*	<0.01**
Rank Index	-0.04	0.18	-0.20	0.84	
Species (long-tailed vs bonnet)	0.41	0.26	1.54	0.12	
Species (rhesus vs bonnet)	0.40	0.25	1.62	0.10	
Species (long-tailed vs rhesus)	0.00	0.18	0.02	0.98	
Affiliation eigenvector	5.52	2.69	2.05	0.04*	0.15
Proximity eigenvector (bonnets)	22.09	7.66	2.88	<0.01**	<0.01**
Proximity eigenvector (long-tailed)	6.22	3.40	1.83	0.07(*)	<0.01**
Proximity eigenvector (rhesus)	8.39	4.00	2.10	0.04*	<0.01**
Proximity eigenvector (long-tailed vs bonnets)	-15.87	7.80	-2.03	0.04*	<0.01**
Proximity eigenvector (rhesus vs bonnets)	-13.70	7.80	-1.76	0.08(*)	<0.01**
Proximity eigenvector (long-tailed vs rhesus)	-2.17	4.69	-0.46	0.64	0.15

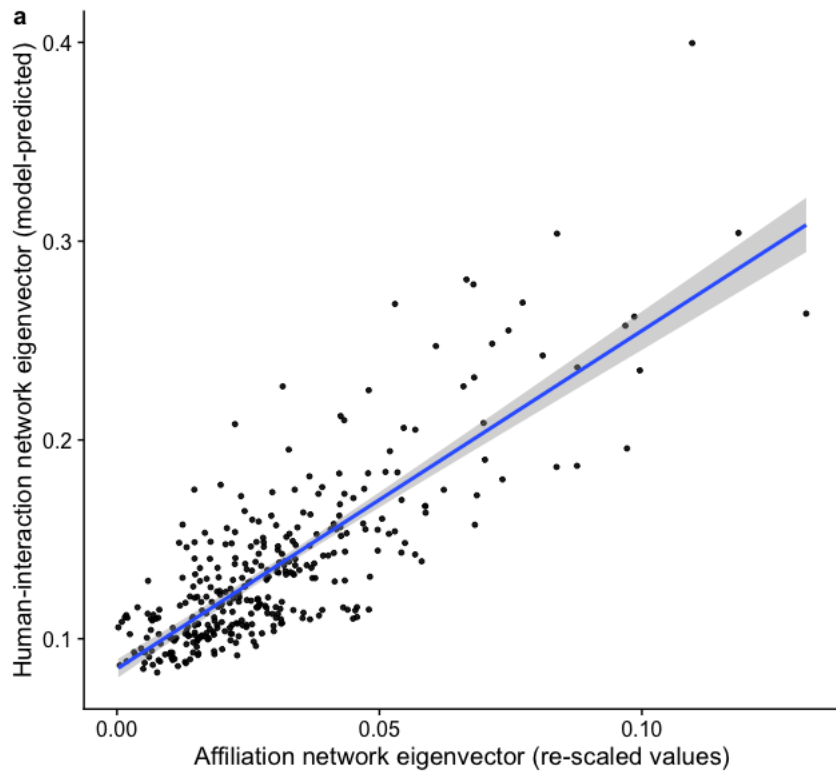
458 **p < 0.01; *p < 0.05

459

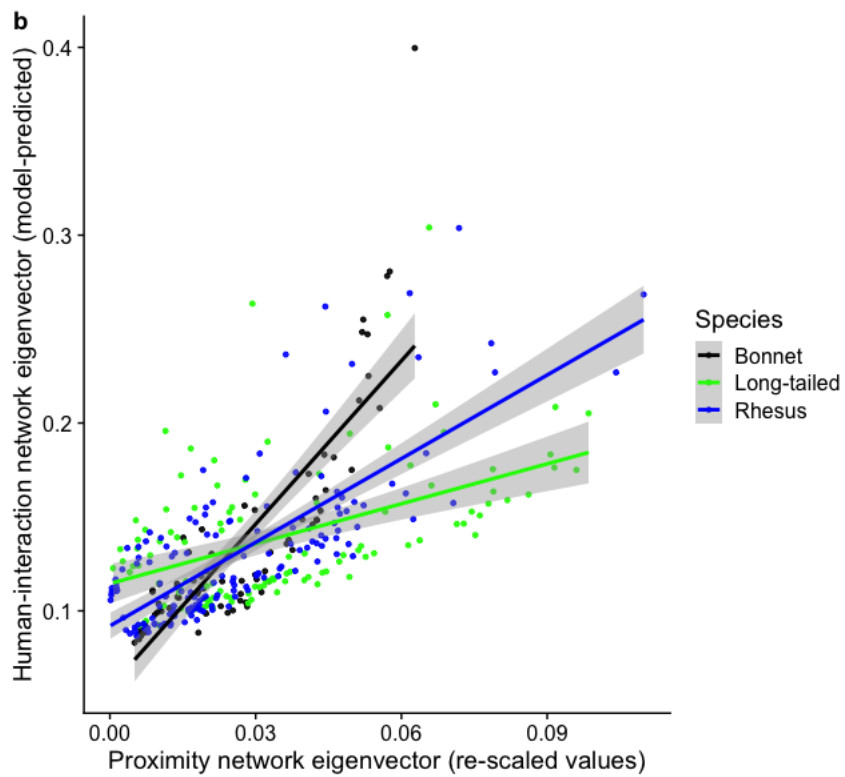
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465 **Figure 4: Effects of (a) affiliation eigenvector centrality and (b) proximity eigenvector**
466 **centrality by species on human-interaction network eigenvector centrality.**

467

468 **Discussion:**

469 For multiple groups of wild macaques living in anthropogenic environments, we used a
470 network-approach to reveal non-random patterns of associations in human-wildlife interactions.
471 Moreover, we revealed that macaques' connectedness within their human-interaction networks
472 were strongly influenced by aspects of their behavioral ecology. Below we discuss our findings,
473 and their implications for understanding the behavioral ecology of human-wildlife interactions
474 from both evolutionary and conservation perspectives.

475 For all macaque groups, human-interaction networks showed a non-random structure,
476 confirming that macaques showed heterogeneous, non-random patterns of using anthropogenic
477 features of their home range and engaging with humans across time and space. This finding
478 provides an important pretext to conducting assessments of whether/how these non-random
479 spatiotemporal associations of wild macaques and humans, are influenced by animal ecology and
480 behavior (as we do in this study). This has important implications both for understanding
481 animals' adaptive responses to dynamic anthropogenic environments, and for conservation- and
482 public health-related initiatives (discussed below). In constructing human-interaction networks,
483 we advanced previous studies that have focused on specific types of human-wildlife interactions
484 (e.g. encounter rates, avoidance, contact-behaviors like aggression and food provisioning), or
485 their overall frequencies of occurrence (reviewed in Balasubramaniam et al. 2020a), to focusing
486 on patterns of human-wildlife associations as revealed by network connectedness. Researchers
487 have been increasingly implementing social network analysis to understand human impact on

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488 animal-animal spatial and social behavior, but not necessarily to model human-wildlife
489 interactions themselves (Snijders et al., 2017; Sosa et al., 2021a). Our construction of human-
490 interaction networks addressed this gap. Indeed, approaches similar to ours may be used to
491 construct other human-wildlife interaction networks in which terrestrial, group-living wildlife
492 populations that overlap with anthropogenic environments (e.g. wild ungulates, elephants, other
493 nonhuman primates like baboons and chimpanzees) may be inter-linked based on their shared
494 spatiotemporal overlap and/or interspecies interactions with humans, livestock, or feral
495 mammals.

496 Macaques' human contact networks were strongly associated with some aspects of their
497 behavioral ecology, but not so with others. For instance, the connectedness of macaques within
498 their human contact networks were strongly associated with their connectedness within networks
499 of affiliative social interactions of short duration, but not so their grooming networks. In group-
500 living primates, affiliative interactions bring proximate benefits such as the reduction of stress
501 levels (Aureli et al., 1999; Shutt et al., 2007), underlie strong alliances between kin and friends
502 (van Hoof & van Schaik, 1992), and are key to the establishment and maintenance of strong
503 long-term social bonds (Silk et al. 2003; Young et al., 2014). Our previous work on these
504 populations revealed how monitoring human activity reduced the time available for macaques to
505 engage in grooming (rhesus macaques: Kaburu et al., 2019b; longtailed macaques: Marty et al.,
506 2019; bonnet macaques: Balasubramaniam et al., 2020b), but not necessarily for other short-
507 duration affiliative interactions like coalitionary support, lip-smacking, and silent bare-teeth
508 displays in non-aggressive contexts which remained unaffected (bonnet macaques:
509 Balasubramaniam et al., 2020b).

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510 One of the primary motivations for monkeys to interact with humans is to obtain
511 anthropogenic foods (Marty et al., 2020). The benefits of within-group social cohesion and
512 tolerance may, at least in part, help offset the potential physiological and health-related costs or
513 risks involved in gaining access to these foods. Thus, we speculate that in anthropogenic
514 environments in which wild primates may routinely face time-constraints, animals may rely
515 more than usual on short-duration affiliative interactions, which may be especially key to
516 maintaining group cohesion and strong ties of social support when animals have to compromise
517 on their grooming time. Such ties of short-duration affiliative interactions may also encourage
518 collective (and perhaps even cooperative) risk-taking as indicated by animals' co-engagement
519 with humans at the same time and space to procure anthropogenic foods. Our finding of strong,
520 consistent (across multiple groups and three species) associations between macaques'
521 connectedness within their short-duration affiliative social networks and their human-interaction
522 networks supports this argument.

523 Human-interaction networks were also influenced by social proximity networks, with the
524 effect sizes being different across species. They were the strongest for bonnet macaques and the
525 weakest for long-tailed macaques, with rhesus macaques falling in-between. Species-typical
526 differences in behavior that is also linked to differences in evolutionary history may at least
527 partly explain these patterns. In comparison to rhesus macaques and long-tailed macaques,
528 bonnet macaques are considered to be more socially tolerant (Balasubramaniam et al. 2012;
529 Thierry, 2007), are less widely distributed and less ecologically flexible (Gumert, 2011; Priston
530 & McLennan, 2013; Radhakrishna & Sinha, 2011), and have had a shorter (in evolutionary time-
531 scales) history of exposure to changing, anthropogenically impacted environments (Gumert,
532 2011; Priston & McLennan, 2013; Radhakrishna & Sinha, 2011). More generally, these patterns

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533 across macaques suggest that in group-living wildlife characterized by more tolerant social
534 systems and/or less ecological flexibility (e.g. bonnet macaques compared to rhesus and long-
535 tails), being near familiar individuals such as close kin or conspecifics may encourage greater
536 propensities among individual animals to take risks in anthropogenic environments.
537 On the other hand, cross-site, or indeed even within-site differences in the distribution and
538 density of anthropogenic factors and (consequently) human-macaque interactions, may also
539 underlie these observed cross-species. For instance, bonnet macaques experienced the overall
540 lowest densities of humans, and their interactions with humans were also more concentrated
541 when the groups were within specific areas (blocks) of their home-range (McCowan,
542 *Unpublished Data*). In comparison, rhesus and (especially) long-tailed macaques were exposed
543 to higher densities of humans, and their interactions with humans were also more widely
544 distributed across the groups' home-ranges (McCowan, *Unpublished Data*). It is therefore likely
545 that rhesus and long-tailed macaques, more so than bonnet macaques, engaged with humans both
546 preferentially while being near their conspecifics, as well as opportunistically when they were
547 not near their conspecifics. More comprehensive tests of these explanations await future research
548 that quantitatively evaluates, rather than controls for (as was done in this study), intraspecific
549 variation within and across groups of the same species.

550 Macaques' sex also had an effect on their connectedness within human-interaction
551 networks: males were more well-connected than females. Sex-based differences may also reflect
552 differences in life-history requirements and the socioecological roles of males and females.
553 While philopatric females usually form the core of macaque social networks, dispersing males
554 tend to be more exploratory, stay in the group periphery, and (consequently) experience more
555 frequent interactions (Balasubramaniam et al., 2020a; Morrow et al., 2019). Moreover, across

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556 group-living mammals, males face high long-term energetic demands pertaining to their life-
557 history requirements of maintaining large body sizes and other physical features (e.g. horns,
558 antlers, canines) that render competitive and reproductive advantages (Clutton-Brock, 2017).
559 Thus, a combination of their exploratory behavior, movement and dispersal, and life-history
560 requirements that may entail greater risk-taking (Balasubramaniam et al., 2020a; Morrow et al.,
561 2019), may explain why males are more central or well-connected within human-interaction
562 networks than females.

563 One methodological limitation in our construction of human-interaction networks
564 concerned the lack of more precise information on these interactions. Although we contained the
565 assignment of links based on interactions within the same block and time-frame, the construction
566 of more conservative, albeit more sparsely-connected, human-interaction networks may have
567 been possible if we had restricted links to interactions that occurred between macaques and the
568 same human(s), and at the same precise GPS location. Collecting more precise geospatial data on
569 human-macaque interactions would be a vital next step. Moreover, implementing multi-level
570 approaches (Finn et al., 2019) to capture potential heterogeneity in human-interaction patterns
571 across different spatial (blocks) and temporal (observation windows) layers was also beyond the
572 scope of this study, but another important next step. Finally, our results may have been impacted
573 by spatiotemporal variation in human density, which, through affecting the overall frequencies of
574 human-macaque interactions, may also impact the connectedness of macaques within their
575 human-interaction networks. We will assess this possibility in a future assessment of
576 intraspecific variation in these networks.

577 Our study has important implications for the conservation and management of human-
578 wildlife interfaces. Macaques that are more well-connected within their human-interaction

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579 networks, because of their coming into contact with more people across time and space, may be
580 targets of interventions that move human-primate interactions from conflict towards coexistence
581 (Nyhus, 2016). Human-wildlife interfaces, now more so than ever before, are also widely
582 recognized as ‘hotspots’ for the transmission of zoonotic and emerging infectious disease,
583 including SARS-CoV-2 (Cunningham et al., 2017; Townsend et al., 2020). From an
584 epidemiological perspective, it is now well-established that animals that are central within their
585 contact social networks may function as within-group ‘superspreaders’ of infectious agents
586 (Craft, 2015; Drewe & Perkins, 2015). Similarly, it is likely that macaques that are central within
587 human-interaction networks may be disease ‘superspreaders’ both within wildlife systems and
588 across human-wildlife interfaces, making these animals particularly important targets of disease
589 intervention strategies like vaccination and antibiotic treatment (Rushmore et al., 2014). Indeed,
590 our finding of a lack of association between macaques’ human-interaction networks and contact
591 social grooming networks suggests that human-interaction and social contact networks may offer
592 somewhat independent socioecological pathways for disease spread. Assessing the vulnerability
593 versus resistance of both types of networks to zoonotic transmission and disease outbreaks would
594 therefore be vital from conservation and public health perspectives.

595

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607

608 **Author Contributions:**

609 K.N.B (first- and corresponding-author), under the supervision of B.M. (last-author), took
610 the lead in in the study design, supervision of data collection, and the conductance of data
611 analysis and manuscript writing. B.A.B. and E.B.M. were involved in the study design and
612 manuscript writing. P.M., S.S.K., and M.A. all helped design the study, supervised data
613 collection, and participated in manuscript writing. N.R., A.I., S.A.M.S., L.M., S.R., and U.K.
614 helped formulate and implement data collection protocols in India and Malaysia, and participated
615 in manuscript writing as co-authors. B.M. supervised the entire study.

616

617 **Data Availability:**

618 The data used for this manuscript is available with the corresponding-author, and will be made
619 available to reviewers upon request. It will be made publicly available through an online
620 repository if or when the manuscript is accepted for publication.

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