1   **Time to leave: Computations of when to end a social interaction depend on opportunity costs,**
2   **depression, and loneliness**

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8   Abstract

9   Positive social relationships are vital for mental health. There is an ever-increasing understanding of
10   the cognitive and computational mechanisms that underlie how we process others' behaviours during
11   social interactions. Yet fundamentally many conversations, partnerships and relationships have to
12   end. However, little is known about how people decide *when* to leave. Theories of decision-making
13   posit that people stop a behaviour in favour of another based on evidence accumulation processes,
14   shaped by the value of alternative behaviours (opportunity costs). Do people compute evidence to
15   leave social interactions based on the opportunity costs of connecting to others? Here, in a novel
16   economic game, participants made decisions of when to leave partners in social environments with
17   different opportunity costs for moving on. Across four studies we find that people leave partners more
18   quickly when the opportunity costs are high, both in terms of the average generosity in the
19   environment and the effort required to connect to the next partner. People's leaving times could be
20   accounted for by a fairness-adapted evidence accumulation model, with a lower threshold for leaving
21   in high opportunity cost social environments. Moreover, decisions to leave were modulated by
22   depression and loneliness scores, which were linked to an interaction between the fairness of a
23   partner and the opportunity cost of the social environment. These findings demonstrate the cognitive
24   and computational processes underlying decisions to leave social interactions, and highlight that
25   loneliness and depression may be linked to an atypical dynamic allocation of time to social
26   interactions.

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Introduction

Positive interpersonal relations are fundamental to mental health[1–7]. To understand what underlies positive social interactions, research in social psychology, neuroscience, psychiatry, and behavioural economics has examined how we react to others' behaviours during interactions. For example, economic games have been fruitful in examining the extent to which we punish others when they are being unfair, uncooperative or untrustworthy[1–9]. Yet much of this research ignores one of the most common responses to another's actions: we leave. In the real-world even if we feel unfairly treated, many reactions to others' behaviours such as punishment can be unwise, or simply not possible. For example, imagine being at a party where a work colleague starts making statements you disagree with. While you may feel tempted to rebuke them, this could have significant, negative personal consequences in the future. So instead, people often decide to end that social interaction. How do people evaluate that an interaction is declining in value, and decide when it is time to leave?

Despite almost all conversations, and many relationships, necessarily ending at some point[17], little is known about how people decide when to leave a social interaction. Existing research has focused on what content leads to people leaving a conversation, the phrases used to end them, or examined how misaligned people's preferences are for the duration of an interaction[17–20]. However, few studies have examined the computational processes underlying how we ascribe value to a social interaction, evaluate that it is declining, and make a decision to move on from it. Strikingly, such decisions approximate problems studied in decision science and behavioural ecology about when animals stop one activity, in favour of another[21,22]. Therefore we propose that decisions to leave a social interaction should depend on similar decision-making mechanisms, and in particular on opportunity costs.

An opportunity cost is typically defined as the value of alternative, or foregone, activities one could be engaged in[22–25]. Theories of opportunity cost processes are particularly powerful because they make specific predictions about how to optimally allocate time[21,24,26,27], rather than focusing on binary choices between options, as is more common in cognitive and decision sciences[22,28,29]. That is, the time you spend engaged in one activity is influenced by the value of the time you could spend in others. In doing so, they formalise the processes underlying when to leave an activity. Yet, such theories have rarely been applied to research in social cognition, and in particular to how people make decisions to leave a social interaction[28]. Here, we suggest that the quality of one's social environment shapes the opportunity cost of other possible interactions one could have, and thus how long people should spend voluntarily interacting with others.

Opportunity cost theories assume that people will allocate time to different behaviours in order to maximise a desired resource[21,30–32]. For example, imagine a bee foraging for pollen. As it remains at a

62   flower, the amount of pollen left available declines. To maximise intake, it needs to decide when is

63   the best time to leave and travel to the next flower. To do this optimally, it must compare the value

64   of the pollen it is currently getting, to the average value of pollen intake it could get from other flowers

65   in the environment – the opportunity cost. As such, in a rich environment with a high opportunity cost

66   where lots of the other flowers give out lots of pollen, it should spend less time interacting with each

67   flower than when the opportunity costs are low. Many species' behaviours conform to this principle

68   of leaving sooner from locations in rich environments when collecting rewarding resources[26,27,31–36].

69   Human behaviours are also similarly sensitive to opportunity costs[27,28], including for eye movements[37],

70   the allocation of cognitive control[25], and time spent online[38,39]. Recent theoretical accounts suggest

71   that opportunity cost based decision-making can be unified with computational and neural processes

72   that underlie evidence accumulation[40,41]. That is, evidence is accumulated towards a decision to leave,

73   which is triggered when a threshold is reached [40,41]. Therefore, we hypothesised that in richer social

74   environments, people will end interactions with others more quickly due to changes in the evidence

75   accumulation process.

76   Notably, psychiatric symptoms such as depression and loneliness are linked to less time being spent

77   in positive social interactions, and poorer interpersonal relationships[1,4,42]. Risk factors for depression

78   and loneliness include unhelpful cognitive processes at the individual-level, such as heightened

79   sensitivity to others' threatening and unfair behaviour[1,43–46]. Yet there are also environmental risk

80   factors, such as poorer neighbourhood cohesion and less supportive social networks, that affect who

81   a person is likely to get the opportunity to interact with[4,6,45,47,48]. Strikingly, an opportunity cost account

82   could provide a normative explanation for how much time people spend in social interactions and how

83   they adapt this as the quality of the social environment changes. That is, in poor social environments

84   it might be adaptive to tolerate slightly lower quality social interactions than in a richer one i.e. you

85   might spend less time talking to a slightly disagreeable colleague at a party where everyone else is

86   much more agreeable. Thus, maladaptive opportunity cost processes underlying decisions to leave

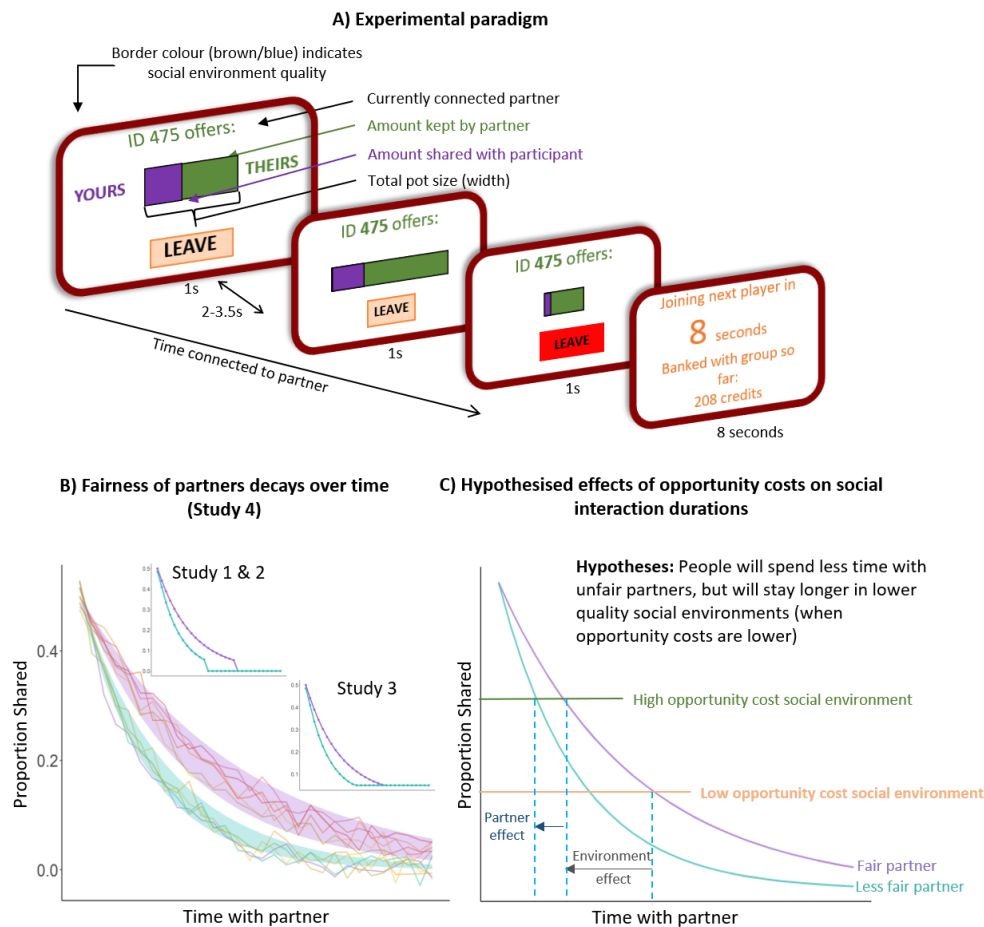87   may be a hallmark of increased loneliness and depression.

88   We developed a novel paradigm to test the notion that people decide to end social interactions that

89   are declining in value depending on opportunity costs, and evidence accumulation processes. Unlike

90   other economic games, in this task participants' only decision was when to leave one social interaction

91   in favour of another (**Fig.1; Supplementary figure 1**). Specifically, participants were connected in one-

92   to-one interactions with a partner. Each interaction took the form of repeated decisions from the

93   partner about how much of a pot of money to share with them, similar to repeated rounds of the

94   dictator game[49]. When a participant no longer wished to be connected to that partner they could

95   voluntarily leave, waiting eight seconds to connect to a new, different partner. To change the value of

96   interacting with different partners, we manipulated their fairness – the proportion of the pot they

97   were sharing[10,11,13,50,51]. Some partners' fairness decayed at a faster rate than others over time – similar

98   to decays in fairness observed in multi-round economic games and in real-world social

99   interactions[52,53]. Participants engaged in these interactions during five-minute periods in different

100   'social environments', which differed in the opportunity costs of moving on. In studies one, two and

101   four we manipulated the 'average generosity', changing the proportion of fair or less fair partners in

102   each environment. In study three we altered how much effort needed to be exerted during the eight-

103   second delay in order to connect to the next partner [28,54,55]. This created low opportunity cost

104   environments, where the majority of partners were unfair or where it was effortful to connect the

105   next partner, and high opportunity cost environments where most partners were fair or it was low in

106   effort to connect to a new partner.

107   Across four studies we demonstrate and replicate that the length of time people spend interacting

108   with others increases when a partner is fairer, but also increases in low quality social environments

109   with lower opportunity costs. Moreover, we found that distributions of time spent connected to

110   partners could be accounted for by a fairness-adapted evidence accumulation model, with a higher

111   threshold when the opportunity costs were low. Lastly, self-reported depression and loneliness

112   interacted with the fairness of the partner, and the generosity of the environment, influencing leaving

113   times. These findings support the notion that during social interactions we build evidence towards

114   decisions to leave in a manner that is shaped by the opportunity cost of the alternatives. Moreover,

115   aberrant processing of the variables that underlie decisions to leave may be a marker of the

116   interpersonal challenges related to variability in loneliness and depression leading to less time being

117   allocated to positive social interactions.

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Results

To test an opportunity cost based account of how people dynamically allocate their time to interacting with different people and make decisions to leave social interactions, we conducted four studies. In each study, participants were connected to an anonymous partner and made decisions of when to leave that partner to connect to another (**Fig.1, Supplementary Fig.1**). While connected, they saw how the partner decided to share pots of money of different total magnitudes, with the fairness of these decisions – the proportion of the pot shared – decaying at different rates (creating fair and unfair partners). Importantly, pot sizes were manipulated, such that on average, all partners were equal in the total monetary value that could be obtained while being connected to them. As such, any decision to leave was economically sub-optimal, reduced the amount of money that would be earned, and thus indicated sensitivity to fairness. During the task, participants spent multiple blocks lasting five minutes interacting with partners in different social environments. Across blocks, we manipulated these environments to create high or low opportunity costs for switching between partners. This was either by altering the average generosity – the proportion of fair and unfair partners (Studies 1, 2 & 4) – or the effort required to switch partners (Study 3). Across studies we examined participants' "leaving time", the amount of time they spent connected to partners, as a function of the fairness of the partner and quality of the environment. (**Fig. 1** and **Methods**). An opportunity cost based account predicts that people should spend more time with fairer partners, but should leave partners sooner when in high quality (generous or low effort) environments (**Fig.1C**).

A) Experimental paradigm

Border colour (brown/blue) indicates social environment quality

ID 475 offers:

Currently connected partner
Amount kept by partner
Amount shared with participant
Total pot size (width)

YOURS | THEIRS

LEAVE

1s

2-3.5s

Time connected to partner

ID 475 offers:

LEAVE

1s

ID 475 offers:

LEAVE

1s

Joining next player in

8 seconds

Banked with group so far:
208 credits

8 seconds

B) Fairness of partners decays over time (Study 4)

Study 1 & 2

Study 3

Proportion Shared

Time with partner

C) Hypothesised effects of opportunity costs on social interaction durations

Hypotheses: People will spend less time with unfair partners, but will stay longer in lower quality social environments (when opportunity costs are lower)

Proportion Shared

High opportunity cost social environment

Low opportunity cost social environment

Partner effect

Environment effect

Fair partner
Less fair partner

Time with partner

138

Figure 1: A) Experimental paradigm. Participants were connected with partners (indicated by numerical ID numbers). Partners made decisions about how much to share out of different pots of total credits of different sizes, indicated by the width of a bar on the screen. The amount being shared was purple, and amount kept by the partner shown in green. Participants' task was to decide when to leave a partner to connect to another. When participants chose to leave, they experienced an eight second delay during which they were shown the amount of credits collected in the environment so far. Participants joined different virtual "groups" of potential partners for five-minute blocks, creating different social environments. This information was indicated by a coloured border for the entirety of blocks and an instruction screen between blocks. For variations in design for studies 1 – 3, see supplementary materials. **(B)** The decisions by partners were experimentally controlled with different rates of decline in fairness – the proportion shared. The lines represent examples of proportions shared by partners over time. Studies 1,2 and 3 (inset) had only two types of partner. Study 4 had multiple partners, with noise surrounding the rates of decay of fairness. The purple shaded area represents proportions shared from "fair" partners, the green shaded area represents proportions shared by unfair partners. **(C)** An opportunity cost account predicts that people will leave sooner from less fair (teal line) than fair (purple) partners, but also that it will depend on the opportunity cost afforded by the social environment. To manipulate opportunity costs participants for studies 1, 2 and 4, environments differed by their average generosity, determined by the proportion of fair or unfair players included in the virtual group. In study 3, they differed by the amount of effort (a high or low number of button presses) to be completed before being connected to a new partner. When effort was low, or average generosity high (green line), the opportunity cost was higher and thus it is predicted people would leave partners sooner than when the opportunity cost was low (orange).

139   People switch partner more frequently in more generous social environments

140   In Study 1 (n = 19) and Study 2 (n = 25), the social environment was manipulated by controlling the

141   proportion with which participants would encounter two different types of partner, who differed by

142   the rate at which the fairness of their sharing decisions decayed. There were two types of

143   environment: high and low generosity, which differed by the ratio of fair to unfair partners (75:25

144   high; 25:75 low). To test our hypotheses that participants would spend less time interacting with unfair

145   partners than fair partners, and that they would spend less time with partners in a high generosity

146   environment than a low generosity environment, we carried out a linear mixed-effects analysis. This

147   model comprised time spent interacting as the outcome variable, and partner-type (fair or unfair),

148   environment generosity (high or low), and their interaction, as predictors. We predicted main effects

149   of partner-type and environment, but no interaction, in line with opportunity cost theories[27,54].

150   In Study 1 (**Fig.2A**), we found significant main effects of partner-type and environment, with

151   participants spending less time interacting with unfair partners than fair partners, and less time

152   interacting with partners in a high generosity environment than in a low generosity environment

153   (partner-type: b = -13.86, SE = 1.77, $t_{(17.88)}$ = -7.82, $p < 0.001$; $X^2_{(1)}$ = 61.77, $p < 0.001$; environment: b =

154   3.50, SE = 1.53, $t_{(17.95)}$ = 2.28, $p = 0.035$; $X^2_{(1)}$ = 5.37, $p = 0.020$). There was also a significant interaction

155   (partner-type x environment: b = -3.53, SE = 1.35, $t_{(909.74)}$ = -2.26, $p = 0.009$; $X^2_{(1)}$ = 6.88, $p = 0.009$), such

156   that the difference between high and low generosity environments was statistically significant for fair

157   (b = -5.27, SE = 1.67, $t_{(25)}$ = -3.157, $p = 0.004$), but not unfair (b = -1.74, SE = 1.69, $t_{(25.9)}$ = -1.031, p =

158   0.3121) partners.

159   Partner-type and environment effects remained significant even when excluding decisions that were

160   made after fairness had decayed to zero (**Supplementary results and Supplementary Table 2**). In

161   addition, we also performed a similar mixed-effects model with the same predictors, but using the

162   fairness (proportion shared) at the time of leaving as the outcome variable. We found the same

163   pattern of results, with main effects of partner-type and environment, but no interaction between

164   them (**Supplementary results and Supplementary Table 3**). Notably this behaviour was not

165   economically rational, as leaving a partner led to an eight second period where no reward was being

166   collected. The patterns of behaviour outlined above therefore also led to people earning less money

167   from unfair partners (by leaving them earlier) and earning less money in the high opportunity cost

168   environments (**Supplementary results and Supplementary Table 4**).

169   In Study 2 (**Fig. 2B**) we sought to replicate these findings, using a sample size (n=25) selected based on

170   power calculations from Study 1 (**Methods**). We replicated the main effects of partner and social

171   environment (partner-type: b = -13.38, SE = 1.54, $t_{(23.74)}$ = -8.69, $p < 0.001$; $X^2_{(1)}$ = 75.48, $p < 0.001$;

172 environment: $b = 3.75$, $SE = 1.42$, $t_{(23.20)} = 2.64$, $p = 0.015$; $X^2_{(1)} = 6.97$, $p = 0.008$), but found no

173 interaction (partner-type x environment: $b = -0.64$, $SE = 1.41$, $t_{(1166.58)} = -0.46$, $p = 0.649$; $X^2_{(1)} = 0.21$, p

174 $= 0.649$). Partner-type and environment effects also remained significant even if decisions after

175 fairness had decayed to zero were excluded (**Supplementary results and Supplementary Table 2**). A

176 mixed-effects model with fairness at the time of leaving as the outcome variable showed the same

177 pattern of results, with main effects of partner-type and environment (**Supplementary results and**

178 **Supplementary Table 3**). These patterns of behaviour therefore also led to people earning less money

179 from unfair partners - by leaving them earlier - and earning less money in the high-opportunity cost

180 environments (**Supplementary results and Supplementary Table 4**).

181 Taken together, these studies suggest that people's decisions to leave a social interaction are made

182 based on both how fair that person is behaving, as well as the opportunity costs of the social

183 environment, with more generous environments favouring leaving a partner sooner.
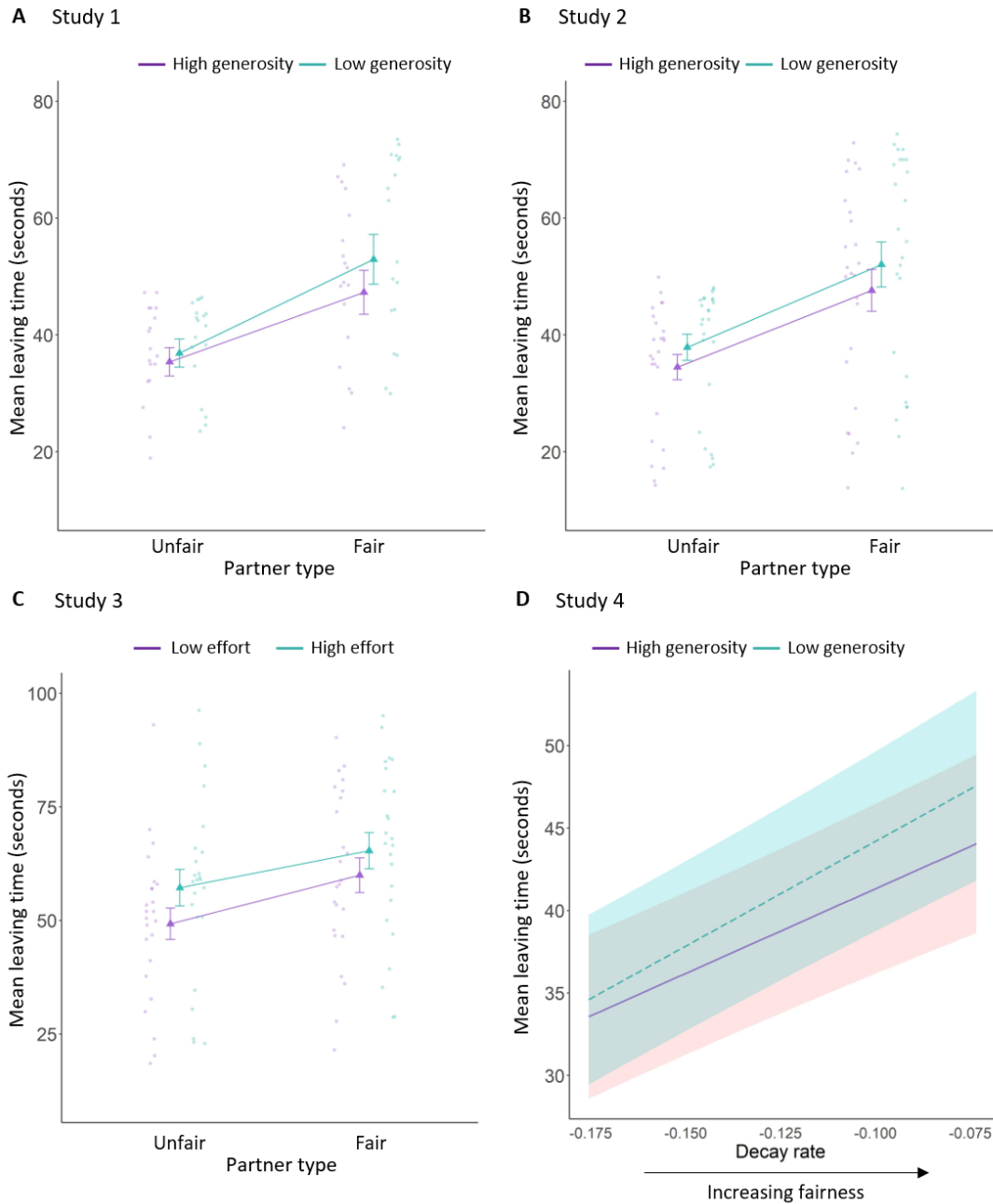
Figure 2: Mean leaving times – time spent connected before deciding to leave – with partners of different types and in the different quality social environments. There were significant main effects of partner-type and environment in all four studies. In all studies participants spent more time connected with fairer partners, but less time with partners when the opportunity cost of the environment was high (i.e. when the group was generous or when it was low effort to connect to another partner). Means from study 1 **(A)**, study 2 **(B)** where the social environment quality was defined by average generosity, high (purple) and low (teal). In study 3 **(C)** the social environment quality was defined by the effort – the number of button presses – required to connect to the next partner. For study 4 **(D)**, partner type was a continuous variable, with shaded regions representing 95%CIs. Points represent individual participant means, triangles represent the summary means with error bars of ±1SE.

People switch partners more frequently when less effort is required to do so

Previous research has suggested that opportunity costs are influenced not only by the average benefits available from alternatives in the environment, but also, the costs that must be incurred to switch from one activity to another[55]. When the cost to leave and explore is higher, the value of alternatives is reduced. This is particularly true for the effort of travelling to seek out alternatives[54–58]. Thus, in Study 3 we examined whether the effort required to switch from one partner to another influenced how long people spent connected. We tested the hypothesis that participants would spend less time interacting with partners when there were less effort costs to switch between interactions. As with Study 1 and Study 2, there were two different types of partner (fair and unfair), but in this study the ratio was 1:1 in both environments. As such, there were no differences in average generosity. Instead, effort costs were introduced to the task, which differed between environments. When participants left a partner, they were required to exert effort during the eight second delay. This effort was operationalised as high or low numbers of repeated button presses, calibrated to a participant's own maximum numbers of button presses. Each environment required either the high or low effort, defined as 80% and 20% of the participants' maximum, respectively.

Once again we found significant effects of partner-type and environment (**Fig.2C**). Participants spent less time interacting with unfair partners than fair partners (partner-type: b = -9.10, SE = 1.38, $t_{(812.58)}$ = -6.60, p < 0.001; $X^2_{(1)}$ = 44.30, p < 0.001), but also spent less time connected to partners when less effort was required to switch between them (environment: b = 6.13, SE = 1.38, $t_{(812.68)}$ = 4.45, p < 0.001; $X^2_{(1)}$ = 19.53, p < 0.001). There was no significant interaction (b = 1.45, SE = 2.75, $t_{(812.32)}$ = 0.53, p = 0.599; $X^2_{(1)}$ = 0.28, p = 0.599). A mixed-effects model with fairness at the time of leaving as the outcome variable showed the same pattern of results, with main effects of partner-type and environment (**Supplementary results** and **Supplementary Table 3**). Thus, participants spent less time with less fair partners, but spent longer interacting with a partner if it was effortful to connect to another.

Depressive symptoms and loneliness alter sensitivity to partner fairness and social environment quality

In Study 4, as well as replicating the effects from the previous studies there were three additional aims: (i) To better represent real-life social behaviours, we included multiple different partner types, rather than just two (fair and unfair). We created a continuum of 17 decay rates describing the rate at which partners' sharing decisions became less fair. Additionally, we added noise around the decay curve so the change in fairness was less predictable and to make each partner's pattern of decisions unique (**Fig.1 B**). (ii) to test hypotheses relating to depression and loneliness we collected a larger

218 sample (n = 81) in an online version of the task, and in addition to completing the task, we had
219 participants complete the Depression, Anxiety and Stress Scale (DASS)[3] as well as the De Jong Gievald
220 loneliness scale (DGLS)[59], (iii) we also included additional blocks, in order to increase the number of
221 samples per participant. This allowed us to fit evidence accumulation models to data without over-
222 fitting to individual data or pooling data across participants (see below).

223 We initially defined a mixed-effects statistical model equivalent to those in Study 1 and Study 2, except
224 with the partner-type (fair/unfair) replaced with the continuous "decay rate" of the partner.
225 Replicating the previous results, there was a main effect of both the decay rate of the partner and
226 environment (partner: b = 3.80, SE = 0.43, $t_{(65.13)}$ = 8.79, p < 0.001; $X^2_{(1)}$ = 76.23, p < 0.001; environment:
227 b = 2.22, SE = 0.82, $t_{(58.46)}$ = 2.72, p = 0.009; $X^2_{(1)}$ = 7.33, p = 0.007), with no significant interaction (b =
228 0.81, SE = 0.44, $t_{(5362.64)}$ = 1.83, p = 0.068; $X^2_{(1)}$ = 3.33, p = 0.068). A mixed-effects model with fairness
229 at the time of leaving as the outcome variable showed the same pattern of results, with significant
230 effects of partner and environment (**Supplementary results and supplementary Table 3**).

231 Next, we included scores from the DASS-21 into the mixed-effects model with leaving time as the
232 outcome variable. The DASS-21 has three subscales (depression, anxiety and stress). Six participants
233 did not go on to complete the questionnaires, making the sample size for this analysis n = 75. Model
234 comparison showed that a mixed-model with just the depression scores had a better fit than those
235 additionally including anxiety and stress. As such the model presented here included the main effects
236 of partner type (decay rate), environment, and depression, as well as the two-way and three-way
237 interactions. This model showed the main effects of partner-type and environment as that presented
238 above (partner: b = 3.85, SE = 0.47, $t_{(60.02)}$ = 8.27, p < 0.001; $X^2_{(1)}$ = 68.56, p < 0.001; environment: b =
239 2.03, SE = 0.85, $t_{(52.29)}$ = 2.38, p = 0.021; $X^2_{(1)}$ = 5.68, p = 0.017). Indluing depression in the model resulted
240 in a change in the interaction effect, with the two-way partner-by-environment interaction becoming
241 signifcant (b = 0.86, SE = 0.46, $t_{(4896.88)}$ = 1.89, p < 0.059; $X^2_{(1)}$ = 4.00, p = 0.046). Additionally, we found
242 a three-way interaction between partner, environment, and depression score (**Fig.3**; b = 1.04, SE =
243 0.48, $t_{(4885.67)}$ = 2.18, p = 0.030; $X^2_{(1)}$ = 4.73, p = 0.030). The main effect of depression, and all other two-
244 way interactions were non-significant (ps > 0.05). We found exactly the same pattern of results when
245 including loneliness scores instead of depressions scores. There was a three-way interaction between
246 partner, social environment, and loneliness score (b = 0.56, SE = 0.26, $t_{(4892.66)}$ = 2.18, p = 0.030; $X^2_{(1)}$ =
247 4.73, p = 0.030). The main effect of loneliness, and all two-way interactions were non-significant (ps >
248 0.05). We were unable to include both depression and loneliness in the same statistical model due to
249 their high correlation (Spearman's rho = 0.59).

250 Post-hoc analyses indicated that there were partner-by-depression and partner-by-loneliness

251 interactions in the low generosity environment, but not in the high generosity environment (**Fig.3**). In

252 the low generosity environment, participants with higher depression (and loneliness scores) spent less

253 time interacting with unfair partners than those with low depression (or loneliness) scores. Moreover,

254 participants with higher depression and loneliness scores spent a similar amount of time interacting

255 with unfair partners in both types of environment, which was not the case for participants with low

256 depression scores. Notably this effect could not be explained by behaviour being more economically

257 rational, as overall earnings for the task were not predicted by depression or loneliness scores

258 (**Supplementary results and supplementary Table 5**).

259 As such, in line with our hypotheses, these results suggest that depression and loneliness are linked

260 to atypical decisions to leave a social interaction, and in particular to atypical integration of the

261 fairness of someone's behaviour with information about the opportunity costs of the social
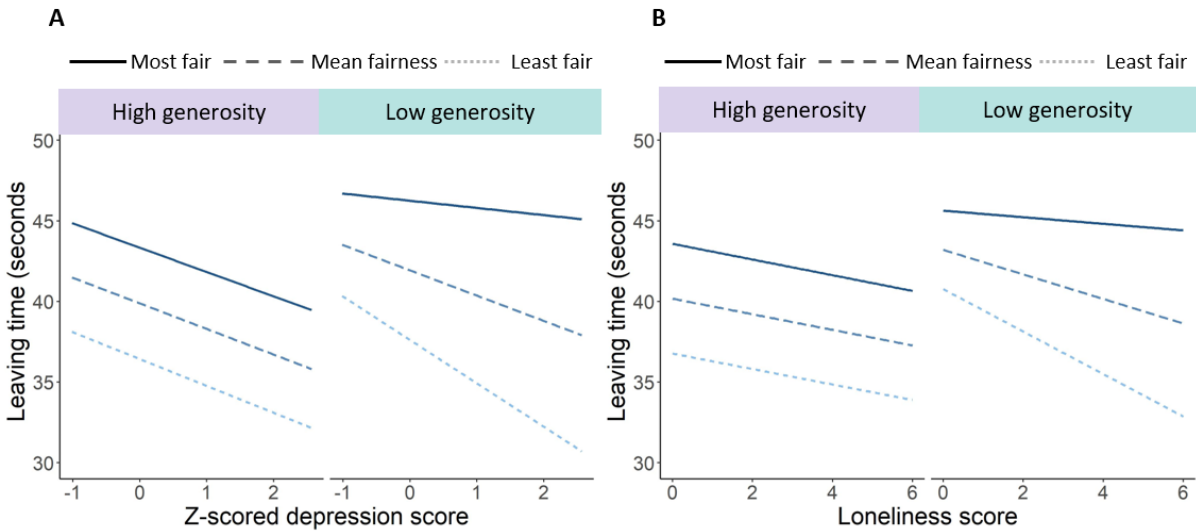
262 environment.

263

264 **Figure 3:** Study 4 results. **A)** Depicts the significant three-way interaction between partner-type,

265 environment, and depression **B)** Depicts the three-way interaction between partner-type,

266 environment, and loneliness. In both cases, in low generosity environments, participants with higher

267 self-reported scores spent less time interacting with more unfair participants (three-way interaction

268 $p = 0.030$ for both measures). Thus, higher depression and loneliness ratings were linked to different

269 sensitivity to the fairness of partners and the quality of the social environment on decisions to leave

270 social interactions. 'Most fair' and 'least fair' refer to mean fairness plus 1SD and mean fairness minus

271 1SD, respectively.

272 A fairness-adapted evidence accumulation model accounts for decisions to leave

273 To better understand the computational processes underlying how people evaluate the fairness of a

274 social interaction with information about the opportunity costs afforded by the social environment,

275 we modelled decisions to leave partners as an evidence accumulation process using an adapted drift

276 diffusion model (DDM). This model assumed that participants are constantly and noisily accumulating

277 evidence over the course of the interaction, and that the decision to leave is triggered when the

278 amount of evidence reaches a threshold level (**Fig. 4**)[40]. The evidence accumulation process is

279 described by four parameters (see **Methods** for full details): i) an initial starting value (bias); ii) the

280 threshold to be reached; iii) the drift rate, which describes the rate of evidence accumulation; iv) the

281 noise parameter, which describes how noisy the evidence accumulation is. We compared the fits of a

282 standard model (Standard-DDM), which was naïve to the experimental manipulations, to two other

283 models. In the first, the drift in evidence accumulation was modulated by the fairness of each of the

284 partner's sharing decisions (Fairness-DDM). In the second, the magnitude of the reward being shared

285 by the partner at each decision, rather than fairness, was used to modulate the drift in evidence

286 accumulation (Reward-DDM).

287 We fit each of these three models to each participant's distribution of leaving times in Study 4,

288 separately for each social environment. Model comparison (combined BIC across the two

289 environments) revealed that the Fairness-DDM was a better fit to leaving time distributions than the

290 Reward-DDM and Standard-DDM (**Fig.4b**). To further assess the quality of fit of the winning model,

291 we computed correlation coefficients between the average leaving time from the data and the

292 winning model for all participants and for each environment. The Spearman's rho was 0.98 and 0.99

293 for the high and low generosity environments, respectively, indicating good fit. In simulated data

294 (**Fig.4c**), the Reward-DDM failed to account for the fairness of partners, and the Standard-DDM did

295 not predict an environment effect (**Supplementary results**). In contrast, the Fairness-DDM was able

296 to capture both partner-type and environment effects present in the statistical analysis of the data

297 above. When running a linear mixed-effects model on the simulated data from the winning Fairness-

298 DDM, we found main effects of partner-type and social environment, (partner-type: b = -6.54, SE =

299 0.13, $t_{(161900)}$ = -49.827, $p < 0.001$; $X^2_{(1)}$ = 3877.81, $p < 0.001$; environment: b = 1.66, SE = 0.13, $t_{(161900)}$ =

300 12.734, $p < 0.001$; $X^2_{(1)}$ = 688.65, $p = 0.001$; see **Supplementary results and Supplementary Table 4** for

301 the other models).

302 If people were making decisions to leave in line with an evidence accumulation model, but adapting

303 behaviour to the quality of the social environment, we would expect features – the parameter weights

304 – of the model to differ between environments. In line with this, we found a higher threshold

305 parameter in the low generosity social environment compared to the high generosity social

306 environment ($X^2_{(1)}$ = 3.93, p = 0.048). None of the other parameter values differed across social

307   environments (**Supplementary Figure 3**). This suggests that people required more evidence to be

308   accumulated before making a decision to leave in a poor social environment when the opportunity
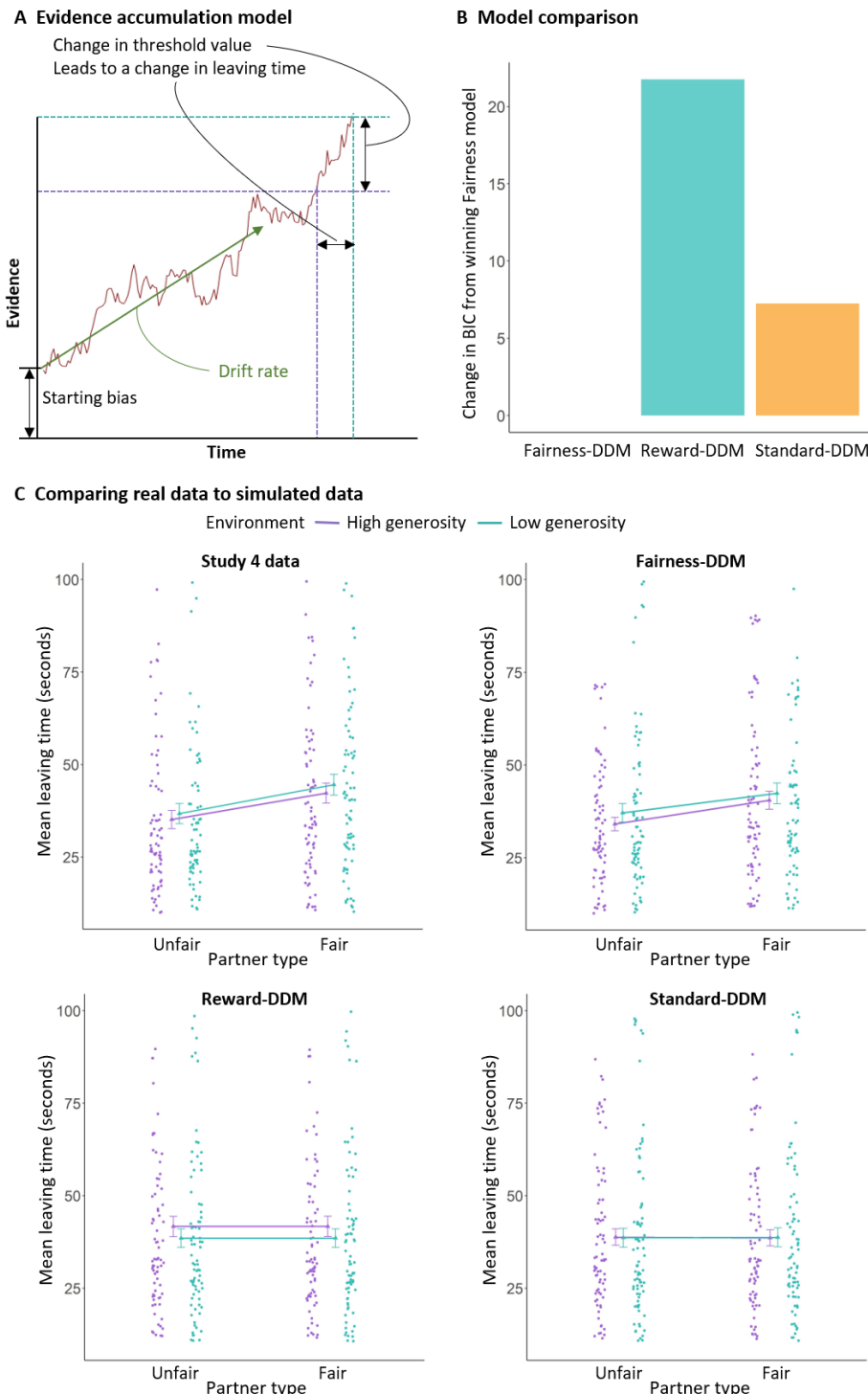
309   costs were low.

310

Figure 4: A) Schematic Representation of evidence accumulation models. In all models evidence accumulated to leave the social interaction over time. The fairness and reward DDMs adapted this accumulation, with the drift multiplied by reward obtained (reward) or proportion or shared (fairness) at the time of each decision by the partner **B)** Model comparison of the three competing models (BIC) showed that the fairness model was best able to explain behaviour compared to the reward and standard DDMs **C)** Plots of the simulated data for each of the three models compared against data from study 4 (top left). Dots represent estimated/actual mean for a participant. Only the Fairness-DDM replicated the effects of partner-type and environment on simulated leaving times. Triangles represent estimated/actual mean across participants. Error bars represent SEM.

314   Discussion

315   We often have to decide whether to leave social interactions. Here we tested the hypothesis that

316   deciding how long to spend in social interactions depends on how fairly we are treated, as well as the

317   opportunity costs of moving on to other people in the environment. To do so, we manipulated the

318   decay of how fairly participants were treated, and the quality of the social environment, in a novel

319   economic game. Across four studies we show that people spend more time with fairer partners, but

320   also spend more time with partners in poor social environments when opportunity costs are low, both

321   when the environment quality was determined by the average generosity of other people and by the

322   effort to connect to another person. In addition, leaving times were related to depression and

323   loneliness, with scores on these measures linked to an interaction between how fairly a partner

324   treated the participant and the quality of the environment. We were also able to capture the

325   computations underlying decisions to leave using an adapted drift diffusion model: the evidence to

326   leave reflected the decaying fairness of the interacting partner, with changes in the quality of the

327   social environment reflected by a different threshold needed to be reached before leaving. Thus,

328   ending a social interaction may rely on evidence accumulation processes that reflect the opportunity

329   costs of moving on in different social environments

330   Importantly, our results suggest that the length of time people spend in an interaction differs as a

331   function of the quality of the social environment, and thus the opportunity cost. This was regardless

332   of whether the opportunity cost was manipulated through changing the average generosity of the

333   environment, or through manipulating how hard people would have to work to connect to another

334   person. These findings align with recent research showing the importance of opportunity costs when

335   making other types of decisions, such as whether to exploit a current location or travel and explore

336   elsewhere to obtain rewards[26,27,36] or how to allocate time to visual searches of social stimuli[37,60].

337   However, unlike in other experiments, in this task participants were sacrificing rewards when making

338   decisions to leave social interactions. This suggests that opportunity costs apply to the value ascribed

339   to the resource one is trying to maximise and not to reward value per se[61,62]. In our experiment the

340   resource being maximised was the time spent in positive, fair, social interactions. Thus, our results

341   suggest that opportunity cost principles can be applied to a much broader range of social decisions,

342   including those that impact how much time we spend in social interactions[28,61].

343   Our results also suggest that at the mechanistic level, similar neural and computational processes for

344   other types of decision problems may also underlie how people end social interactions. We showed

345   that choices in the task could be fitted with an adapted DDM, in which evidence to leave drifted

346   towards a threshold, which when reached, triggered a decision to leave. The parameters used in this

347   model, quantifying a starting bias in evidence, a threshold boundary, the rate of drift of evidence, and

348   noise, are standard within evidence accumulation models[63–65]. Such models have been used to

349   understand the psychological and brain processes guiding perceptual, economic and social decisions,

350   but not previously to how people decide to leave social interactions[64,66]. Although this suggests that

351   there may be normative, domain-general mechanisms that underlie such decisions, there were key

352   differences in the model to a standard DDM. In particular the model was accumulating across the

353   entire time connected to another player, but constantly changing as the fairness of the decisions of

354   the partner changed. This model did better than a DDM in which evidence was simply accumulating

355   over time, indicating that fairness may be a type of evidence that can be accumulated over longer

356   timescales, as has been shown for rewards[40,41]. Moreover, by fitting this model separately to the

357   different social environments, we could show a higher threshold when the model was fitted to the

358   poorer social environment than the richer i.e. when opportunity costs were low. Taken together, these

359   results suggest that decisions to leave a social interaction are contingent on the build-up of evidence,

360   which depends on how much value is currently being ascribed to the social interaction (i.e. how fair it

361   is). However, decisions change depending on the quality of the social environment. Higher quality

362   environments create a lower decision threshold, and thus less accumulated evidence of unfair

363   behaviour is needed before leaving.

364   A plethora of existing work has shown that people value fairness, and will lose out on economic

365   rewards, in favour of being treated fairly[10,51]. In this respect, our participants' behaviour was

366   consistent with that found in economic games. However, existing work had typically examined fairness

367   as a static property, showing that people would punish others at a certain level of disadvantageous

368   inequity – when an amount offered to ourselves in an economic game falls somewhere below

369   50%[10,11,15]. Although some previous studies suggest that the context of a social interaction can

370   influence how likely people are to punish unfair behaviour[67–69], we are unaware of any previous study

371   that directly manipulated the opportunity cost, nor examined how people decide when to leave a

372   social interaction. In doing so, we show that fairness is not processed in an absolute manner. Instead,

373   our results suggest that people adapt how fairly they are willing to be treated based on the average

374   behaviour in a social environment. Indeed, we showed that people would stay longer, and that they

375   would tolerate a lower level of fairness, in an environment where most people were less generous.

376   Such findings suggest that people are moral relativists when it comes to fairness[70,71]. That is, how

377   unfair they perceive an act to be changes based on how likely it is that other people would be similarly

378   unfair.

379   Changing one's principles, such as what one considers as fair behaviour, based on what is the social

380   norm can have potentially wide social and moral consequences[71]. However, our results suggest this

381 behaviour may be typical and adaptive when it comes to allocating time to interacting with different
382 people. Strikingly, we found that decisions to leave social interactions correlated with depression and
383 loneliness. Higher depression and loneliness scores related to atypical patterns of behaviour,
384 particularly in poorer social environments. Higher scores on these measures related to staying longer
385 with fairer partners but less time with the least fair people in the poor environment relative to the
386 rich. As in this task the fairness of partners decayed over time, this suggests that high depression and
387 loneliness may be linked to a tendency to favour staying with individuals who were originally fair, but
388 are no longer acting fairly, specifically in poor environments. Such findings may provide a mechanism
389 for understanding why depression and loneliness have been linked to greater sensitivity to unfair
390 behaviour[43,44], but also risk factors that impact on the quality of social environment[1,6]. In particular
391 our results highlight that a heightened sensitivity to unfair behaviour and being in a poor social
392 environment may be interacting risk factors, leading to the perception of poor social relationships,
393 which is common in depression and chronic loneliness[43,45,47]. As such, our results suggest that being
394 appropriately sensitive to unfair behaviour, but also being a moral relativist in one's behaviour and
395 adjusting to the quality of the social environment is adaptive, and may contribute to mental health.
396 Moreover, these results highlight that interpersonal deficits linked to depression and loneliness may
397 be better understood using decision theories that account for the dynamic allocation of time to social
398 activities.

399 Recent work has sought to examine when people choose to end natural conversations, both in the lab
400 and in real life, and reported that the preferred time to end a conversation rarely aligns across
401 interacting partners[72]. Although many features of the content of conversations will influence their
402 value that go beyond the fairness manipulation deployed in this experiment, our results point to a
403 potential computational explanation for a lack of alignment. Specifically, as noted above, our results
404 point to DDM-related processes underlying such decisions, which also include noise in the evidence
405 accumulation. Moreover, they point to different thresholds being set when one's opportunity costs
406 differ. As such, the chances of two people valuing the conversation equally, having similarly valued
407 alternative opportunities, and aligned random noise in the accumulation of evidence towards ending
408 the conversation are vanishingly small. Therefore, we suggest that the combination of all of these
409 factors make ending a conversation at a mutually agreed point fraught with challenges[20], even before
410 one considers wider social rules, hierarchies, and the challenges with trying to infer the intentions of
411 others.

412 Social interactions do not happen in isolation, and throughout our life we are faced with choices of
413 joining and leaving social relationships, be they friendships, romantic partnerships, work
414 collaborations, or simply ending a conversation. Our results show that the quality of a social

415 environment – its opportunity costs – are crucial for determining when people make the decisions to

416 leave. Such processes appear normative, and guided by evidence accumulation processes, with

417 atypical consideration of opportunity costs a potential mechanism underlying disrupted social

418 relationships in depression and the chronically lonely.

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426   Methods

427   Participants

428   175 participants (mean age = 27.6 (SD 7.6), range 18 – 51; 62% F) were recruited over four studies (see

429   **Supplementary Table 1** for demographics broken down by study). All studies were approved by The

430   University of Oxford Central Research Committee (Studies 1 – 3 reference number R6061/RE001;

431   Study 4 reference number R59122/RE001). Informed consent was obtained from all participants. In

432   studies 1 – 3, participants were recruited through an Oxford University participant database. In Study

433   4, participants were recruited through the online platform Prolific (www.prolific.co). Participants were

434   compensated a flat rate for their time and were also told that they would receive a bonus based on

435   their responses in the task. However, all participants were paid the bonus, to ensure remuneration

436   was ethical, and not based on participants being deceived by the fairness manipulations in the study.

437   The amounts paid to participants were equal across participants in each study (£14).

438   Experimental paradigm

439   *General task structure*

440   In our task we had participants interact with virtual partners in different environments with unlimited

441   potential partners. Participants' task was to decide when to leave a partner, and wait to be connected

442   to another. We manipulated the 'quality' of both partners and of the environments, to examine

443   whether people make decisions based solely on the quality of an ongoing social interaction or whether

444   they also consider the opportunity cost of other potential partners. Given the consistent finding of its

445   importance to healthy social interactions, we used fairness as a proxy for the value of interacting with

446   a partner[10,11,13,50,51]. The general structure of the task was consistent across all four studies.

447   Participants were instructed that they were virtually joining different groups of people for a total of

448   five minutes per group (**Supplementary Figure 1**). Upon joining a group, they started interacting with

449   one partner in that group until the participant decided to leave the interaction and 'travel' to interact

450   with a different partner in the group. The interactions took the form of a repeated economic game,

451   approximating the dictator game, with the participant in the role of receiver. Thus, every 3.5 seconds

452   the participant saw how their partner chose to share a new pot of credits, with varying stake sizes

453   (**Fig.1**). All accumulated credits were added to the participant's bank, which the participants were told

454   would be converted to a bonus payment at the end of the task.

455   Participants were told that decisions were collected from participants of a previous study. The

456   decisions were in fact pre-coded by the researchers. The proportion shared by each partner decreased

457   over time, representing a deterioration in the 'quality' of the interaction, as indexed by its fairness –

458   defined as the proportion of the total pot shared, with 50% being completely fair and 0% completely

459   unfair. The participant could leave the interaction at any time by pressing the spacebar. Following a

460   leave decision there was an eight second delay prior to joining the next partner in the group, during

461   which time participants received no credits, but were informed how many credits they had banked

462   with the group so far. Participants interacted with each group for a total of five minutes. At the end of

463   those five minutes they joined a completely new group of potential partners. When joining each new

464   group, participants were explicitly told what type of group they were joining, and this information was

465   represented throughout their time with each group by the colour of the screen's border (details for

466   each study outlined below).

467   Crucially, while the 'fairness' of each partner's decisions decreased over the course of the interaction,

468   the absolute value of the credits received by the participant on each trial was uniformly distributed

469   around a constant. As such, regardless of the decay in fairness of a partner, or the fairness of others

470   in the group, the average reward obtained was stable across sharing decisions in the experiment.

471   Therefore, the economically rational behaviour in this task is to never leave a partner, unless fairness

472   decays to 0%, as during the eight seconds it takes to connect to another partner there is no financial

473   reward received. Participants were informed that each partner had a finite number of decisions to

474   make, and that if the participant did not leave an interaction they would automatically travel to the

475   next partner when all decisions had been seen, incurring the eight second travel cost. The number of

476   decisions coded of each partner was 30, but participants were not instructed of this. Below we outline

477   task details and variations across the four studies.

478   *Studies 1 and 2*

479   The aim of study 1 was to examine whether the value of a partner and the opportunity cost of the

480   environment influenced how long people spend in a social interaction, and study 2 aimed to replicate

481   this effect. Studies 1 and 2 used the same version of the task. The fairness of partners was manipulated

482   by changing the rate of decay of the fairness of their sharing decisions, and the opportunity cost was

483   manipulated by changing the proportion of fairer players (players with lower fairness decay rates) in

484   two different social environments. A richer social environment, where the majority of partners had

485   the low decay rate, and a poorer social environment where the majority had the higher decay rate.

486   Thus, studies one and two had 2x2 designs, in which we could examine the effect of partner fairness

487   (fair or unfair) and social environment quality (rich or poor) on how long people spent connected to

488   the players before deciding to leave.

489   The proportion shared by each partner followed an exponential decay, as shown in equation 1.

$$p_t = s * e^{(k*t)} \quad (1)$$

490

491 where p_t is the proportion shared on trial t and k is the exponential decay rate. s, the starting value,

492 was set to 0.5 (an equal split) for the purpose of creating the trajectory but the proportion shared of

493 the first decision was replaced by selecting from a random uniform distribution with lower and upper

494 bounds of 0.475 and 0.525. Partners differed in the rate of exponential decay in their levels of fairness.

495 There were two partner types, fair and unfair, with decay rates of -0.125 and -0.2 respectively (**Fig.1**).

496 When the proportion dropped below 0.05, this was replaced with a zero. This has the advantage of

497 ensuring that participants could be excluded for failing to attend, as participants should leave if they

498 are consistently receiving none of the pot. The absolute value of each sharing decision (the credits

499 given to the participant) was randomly sampled from a uniform distribution with lower and upper

500 bounds of 50 and 200, with the constraint that the total sum over six decisions must equal 500. This

501 constraint was included to ensure that, as close as possible, there would be no economically rational

502 reason to prefer one partner over another, regardless of when one chose to leave. Stake sizes were

503 determined by the quotient of the absolute value and proportion shared. Where these stake values

504 equalled zero due to the fairness trajectory dropping to zero, the stake was drawn from a random

505 uniform distribution with lower and upper bounds of 200 and 2000.

506 The environment manipulation in this version of the task was the average generosity of the group.

507 When joining a new group, participants were explicitly told "Most partners shared a [high/low]

508 proportion". Participants were instructed that the partners in each environment were randomly

509 drawn from a large set of possible partners. The average generosity of the subset was then computed

510 and compared to the overall average proportion shared. High generosity therefore meant that the

511 average generosity of the group was greater than the average generosity overall. High generosity

512 groups had a fair-to-unfair partner ratio of 3:1, although partners were not instructed of this ratio.

513 Thus, in every set of four consecutive partners, participants would see three fair partners and one

514 unfair partner (randomly ordered). The reverse was true for low generosity groups. This ensured that,

515 as closely as possible, regardless of how many partners a participant interacted with during the five

516 minutes, the experienced group generosity matched the 3:1 ratio of the group.

517 Participants joined eight groups in total, with four being high, and four being low generosity, making

518 the overall time spent on the task 40 minutes. Partner decisions were created according to the

519 parameters described above depending on their status as fair or unfair, and were pseudo-randomly

520 assigned to groups. This ensured that all participants experienced the same eight groups, but the order

521 in which they saw the groups was fully randomised across participants.

522   Sharing decisions were shown in the middle of the screen (e.g. "98 out of 250") for 3.5 seconds before

523   immediately showing the next sharing decision. When participants chose to leave one partner they

524   were shown a countdown of eight seconds prior to connecting with the next partner.

525   *Study 3*

526   The environment manipulation in this study was the effort required to travel between partners.

527   Previous research has shown that repeated finger movements are considered costly, and people will

528   avoid them, unless associated with beneficial outcomes[73,74]. Here, effort was operationalised through

529   repeated key presses during the 8 second delay. There were two environments, low and high effort.

530   Effort levels were participant-specific. Prior to receiving any instructions on the task, participants were

531   asked to press the right arrow key as many times as possible in 8 seconds. They were asked to do this

532   three times, and the average taken as their maximal effort. The required number of button presses

533   was 20% and 90% of their maximum for the low and high effort environments, respectively. This

534   ensured that participants with greater or lesser fidelity at button presses did not consider the button

535   presses too easy or beyond their capacity to complete. Unless otherwise stated, all other elements of

536   this experiment were consistent with that of studies one and two.

537   In this study the ratio of fair to unfair partners was 1:1, making all social environments equally

538   generous overall. The decay rates were the same as those used for Study 1 and 2. However, in this

539   version of the task the proportion shared never dropped to zero. Instead, all proportions below 0.05

540   were replaced with 0.05. This was to remove the potential confound that any partner effect could be

541   due to economic rationality.

542   Participants joined eight groups in total, with four being high, and four being low effort, making the

543   overall time spent on the task 40 minutes. Partner decisions were created according to the parameters

544   described above depending on their status as fair or unfair, and were pseudo-randomly assigned to

545   groups. This ensured that all participants experienced the same eight groups, but the order in which

546   they saw the groups was fully randomised across participants.

547   *Study 4*

548   The social environment manipulation in this study was average generosity, as per Studies 1 and 2.

549   However, to examine whether results would be consistent when partners showed a much greater

550   range in behaviour, instead of having just two decay rates, the version used in this study had 17

551   different decay rates and noise was injected around each sharing decision. Decay rates for fair

552   partners came from the set of {-0.075, -0.080, -0.085, -0.090, -0.095, -0.100, -0.105, -0.110, -0.115},

553   while those for unfair partners came from the set of { -0.175, -0.170, -0.165, -0.160, -0.155, -0.150, -

554   0.145, -0.140}. The ratio of fair to unfair partners in a high generosity environment was 3:1, with every

555   four consecutive partners containing three decay rates randomly drawn from the set of fair decay

556   rates and one from the set of unfair decay rates. The opposite was true for low generosity

557   environments. In this version of the task, the proportion of the first sharing decision was drawn from

558   a random uniform distribution with lower and upper bounds of 0.47 and 0.53. Each subsequent

559   decision was dictated by the exponential decay associated with the specific partner, but with added

560   noise as shown in Equation 2 below. This noise was added to each decisiondecision of eacheach

561   partner meaning that the trajectory of each partner's sharing decisions was unique and less

562   predictable. All proportions below 0.05 were replaced by 0.05. The absolute value of credits shared

563   on each decision was sampled from a random normal distribution with a mean of 400 and a standard

564   deviation of 30.

565 $$p_t = s * e^{(k*t)} + \delta \quad (2)$$

566 $$\delta \sim N(0, 0.015) \ ,$$

567   where δ is the noise term.

568   In this version of the task, three of the first five partners of each environment were randomly selected

569   to include an attention check. This ensured that even those who experience fewer partners in an

570   environment still encountered these attention checks. For these three partners, participants were

571   asked to press a key between partner decisions once in the first four trials with that partner. They

572   were given 2.5 seconds to do so. Failure to successfully complete an attention check held no

573   immediate repercussions for the participant, but missed attention checks informed exclusion criteria

574   when analysing the data.

575   Visual representation of the sharing decisions in this version differed to previous versions (See Figure

576   1A for details). In order to reduce any potential cognitive load of calculating the proportion shared,

577   the sharing decisions were represented with a horizontal rectangle rather than numerically. The overall

578   size of the rectangle represented overall stake available to the partner for that sharing decision, and

579   a shaded area represented the proportion of the stake shared. This rectangle appeared on the screen

580   for 1 second, followed by a blank screen for a period of time jittered around mean 2.5 seconds, thus

581   making the average time of each trial 3.5 seconds as per the other versions of the task.

582   Participants joined ten groups in total, making the overall time spent on the task 50 minutes. Partner

583   decisions were created according to the parameters described above depending on their status as fair

584   or unfair, and were pseudo-randomly assigned to groups. This ensured that all participants

585 experienced the same ten groups, but the order in which they saw these groups was randomised
586 across participants.

Procedure

588 In Studies 1 – 3, participants attended in-person. They were first shown visual and text instructions for
589 the task before discussing those with the researcher to ensure comprehension. They then completed
590 a practice run which involved spending two minutes in each type of social environment, ensuring that
591 any potential effects of the first environment experienced were minimised[36]. Following successful
592 completion of the task training, participants completed the real version of the task.

593 Study 4 recruited participants online through Prolific. In addition to the task described above,
594 participants in this study also completed the Depression Anxiety and Stress Scales (DASS-21)[3] and the
595 De Long Gierveld Loneliness Scale (DGLS)[59]. The order in which they completed the task and
596 questionnaires was counterbalanced across participants. Following the task instructions, participants
597 were asked a series of comprehension questions. If any questions were answered incorrectly, twice,
598 they were excluded from the analysis (n = 3). Following completion of the comprehension questions,
599 participants completed a two-minute practice run in each type of social environment before
600 proceeding to the task. Upon completion of the task they answered some short debrief questions.

601 The task was coded in PsychoPy version 2020.1.3[75], and implemented through a Windows 10 PC
602 (Studies 1 – 3) or hosted on Pavlovia (pavlovia.org) (Study 4).

Statistical analysis

Statistical models

605 All statistical analyses were carried out using R version 4.0.2[76]. All models were analysed as linear
606 mixed-effects models using the packages *lme4*, *lmerTest*, and *car*, with post-hoc analyses carried out
607 with *emmeans*[77–80]. Data were visualised using the package *ggplot2* and model visualisations used the
608 package *interactions* [81,82].

609 To test our hypotheses, we defined the same model for Studies 1 – 3. The time at which the participant
610 chose to leave an interaction ('leaving time' (LT)) was defined as a continuous outcome variable. If a
611 participant chose not to leave a partner, the LT for that trial was defined as the onset of the final
612 sharing decision (but see exclusion criteria below). Partner and environment types were defined as
613 fixed-effects categorical predictors, with two levels each. We modelled both the main effects and the
614 interaction term. We included a participant-level random intercept, as well as random slopes for each
615 main effect (see Equation 3). The model did not converge when including the interaction term in the

616 random effect structure due to a lack of variance across participants. Contrasts were effect-coded
617 such that the intercept beta represented the grand mean, and the main effect betas represent the
618 effect averaged over the levels of the other main effect. We tested the fixed-effects for statistical
619 significance using a Type II Wald chi-square test. In the text we report the results of the chi-square
620 test as well as the beta values and their *t*-test against zero.

621 $$LT \sim partner * environment + (1 + partner + environment \mid ID) \quad (3)$$

622 Due to Study 4 including multiple decay rates, the partner predictor was a continuous predictor (z-
623 scored decay rate), rather than categorical. The model was the same as that described above in all
624 other respects. To test for relationships between task behaviour, depression and loneliness, we
625 performed two additional mixed-effects models. These models were the same as for the main analysis,
626 with the addition of depression or loneliness scores as z-scored continuous predictors. We tested for
627 all main effects, 2-way interactions, and three-way interactions. It was not possible to include both
628 loneliness and depression within the same model, as scores were too highly correlated (Spearman's
629 rho = 0.65) to examine unique variance associated with each.

630 In this task, not leaving a partner is an economically rational response. However, not actively choosing
631 to leave a partner could also be a sign of inattention. Therefore, in Studies 1 – 3, we implemented an
632 exclusion criterion that participants must have made an equal number of active decisions as there
633 were environments. While this may remove participants from the analysis who legitimately chose to
634 never leave a partner, it is a minimal criterion in order to ensure some engagement in the task (Study
635 1 excluded n = 1; Study 3 excluded n = 1). Study 4 included attention checks. Participants were
636 excluded if they failed more than 25% of attention checks (n = 21). For all studies, we excluded trials
637 where the LT was more than 2.5 standard deviations of the mean, on a within-participant, within-
638 condition basis. Again, this was to protect against lapses in attention.

639 *Sample size justification*

640 We ran the statistical model on 5000 simulated datasets based on the fixed effects and variance of
641 the random effects from the analysis of Study 1. Power for each fixed effect was calculated as the
642 proportion of simulations where p < 0.05. This analysis suggested data from 25 participants would give
643 us over 90% power to detect main effects of partner and environment type, and over 80% power to
644 detect an interaction, with alpha at 0.05. Therefore, we set this as our target sample size for Studies
645 2 and 3. We were uncertain as to a likely effect size for the exploratory analyses examining the role of
646 depressive symptoms in Study 4, so aimed to recruit 100 participants for this study.

647 Drift diffusion modelling

648   We modelled decisions to leave as an evidence accumulation process (EA) process using a drift

649   diffusion model (DDM)[83] . We adapted this EA process based on a recent study[40] that posited that

650   animals make decisions to leave patches (locations) when reward foraging through an EA process that

651   drifts towards leaving throughout a series of events of receiving rewards. This model therefore

652   assumes that an animal will leave a patch when a noisy estimate of the state of the current value of

653   rewards being obtained reaches a threshold. Here, instead of reward, we hypothesised that evidence

654   accumulation would depend on the fairness of each decision from the partner that would guide

655   decisions of when to leave a social interaction. To test this we deployed a model where evidence was

656   based on the proportion shared in each decision from the partner, and compared this two other

657   models, a standard model in which the evidence was accumulated regardless of the decisions by the

658   partner, and a reward based model in which the magnitude of a reward influenced a decrease in

659   evidence to leave.

660   The basic process is described by the equation:

661    $$ dEA = (k - X)\, dt + N(0, \sigma) \quad (4) $$

662   with

663    $$ EA(t) \geq 0 \; \forall t $$

664   where X is a variable that changes over the course of the accumulation. We ran three instantiations

665   of the model which differed by the identity of the input variable X. X could be either fairness, reward,

666   or neither of them. The term (k-X) drives the accumulation, k is a parameter that modulates the

667   input, and $N(0, \sigma)$ is a Gaussian noise term with standard deviation σ. We used dt=0.001 s and

668   assumed that the model makes a decision to leave when the evidence is greater than the threshold.

669   i.e. |EA|>θ (the decision threshold – once reached the participant leaves). We also assumed subjects

670   might have some prior bias toward leaving, represented by a starting bias ε. θ, k, σ, and ε are free

671   parameters of the model that were fit separately to each participants

672   Each version of the model was fitted to the individual participant's leaving time (LT) data using

673   maximum likelihood estimation. Specifically, LT distributions were computed for each participant and

674   condition. This LT distribution was compared to the LT generated by the model through repeated

675   simulations. For a given set of parameter estimates, we estimated the log likelihood (LL) of the data

676   using the following formula:

677    $$ LL = \sum_{i_{cond}=1}^{2} \log(KS\left(LT_{data}^{i_{cond}}, LT_{model}^{i_{cond}} \right)) \quad (5) $$

678   where KS*(p,q)* estimates the probability that two distributions are equal according to the Kolmogorov–

679   Smirnov test (computed using MATLAB function *ktest2* which in turn estimates the predicted

680   cumulative probability through the proportions of the predicted LTs which are less than or equal to

681   any observed LT), i_cond is an index representing the condition (the generosity of the social

682   environment). For each participant separately, we identified the set of model parameters that

683   maximized the LL, by searching over a grid of values: θ = {*int* 1:30}, k = {0.1:1.5, in steps of 0.1}, σ =

684   {0.1:1, in steps of 0.1} and ε = {0:0.8, in steps of 0.2}. These ranges were defined after an initial

685   exploratory analysis over a wider range of parameter values to ensure selecting the ones that

686   produced LT distributions spanning those seen in behaviour. For each set of parameters, we generated

687   LT distributions by running 1,000 simulations of the model (that is, by producing this number of

688   decision trajectories using equation (4) for each environment condition). To further assess the quality

689   of the fits resulting from the best set of participant-specific parameters (those that maximized the LL

690   function in equation (5)), we computed correlation coefficients between the average LT from the data

691   and the model for all participants and conditions.

692   We ran three versions of the model where X would be equal, respectively to

693
$$X(t) = F(t) \qquad (6)$$

694
$$X(t) = a * R(t) \quad (7)$$

695
$$X(t) = 0 \qquad (8)$$

696   Where a was a parameter which was scaling R to match the range of values taken by *F*. As $F \epsilon$ (0,1) it

697   followed that *a = max(R) = 0.01.* The model with *X* described by equation (8) was fitting LT distributions

698   without any input from the task variables, offering a benchmark to compare the other models.

699   We compared the different models computing summed BIC. As a validation of the model comparison,

700   we also looked at the proportion of subjects for which any given model was outperforming the others.

701   Reassuringly, the winning model was also the one the most frequently explained the data better across

702   the population (**Supplementary Figure 2**).

703

Author contributions

Data and code availability

718 Analysis scripts and study data will be made available on the Open Science Framework upon

719 publication.

References

1. Kupferberg, A., Bicks, L. & Hasler, G. Social functioning in major depressive disorder. *Neurosci. Biobehav. Rev.* (2016) doi:10.1016/j.neubiorev.2016.07.002.

2. Robson, S. E., Repetto, L., Gountouna, V.-E. & Nicodemus, K. K. A review of neuroeconomic gameplay in psychiatric disorders. *Mol. Psychiatry* 1 (2019) doi:10.1038/s41380-019-0405-5.

3. Henry, J. D. & Crawford, J. R. The short-form version of the Depression Anxiety Stress Scales (DASS-21): Construct validity and normative data in a large non-clinical sample. *Br. J. Clin. Psychol.* **44**, 227–239 (2005).

4. de Jong Gierveld, J., Van Tilburg, T. & Dykstra, P. A. Loneliness and social isolation. *Camb. Handb. Pers. Relatsh.* 485–500 (2006).

5. Bangee, M., Harris, R. A., Bridges, N., Rotenberg, K. J. & Qualter, P. Loneliness and attention to social threat in young adults: Findings from an eye tracker study. *Personal. Individ. Differ.* **63**, 16–23 (2014).

6. Kemperman, A., van den Berg, P., Weijs-Perrée, M. & Uijtdewillegen, K. Loneliness of older adults: social network and the living environment. *Int. J. Environ. Res. Public. Health* **16**, 406 (2019).

7. Umberson, D. & Karas Montez, J. Social Relationships and Health: A Flashpoint for Health Policy. *Journal of Health and Social Behavior* vol. 51 S54–S66 (2010).

8. Crockett, M. J., Clark, L., Hauser, M. D. & Robbins, T. W. Serotonin selectively influences moral judgment and behavior through effects on harm aversion. *Proc. Natl. Acad. Sci.* **107**, 17433–17438 (2010).

9. Gabay, A. S., Kempton, M. J., Gilleen, J. & Mehta, M. A. MDMA Increases Cooperation and Recruitment of Social Brain Areas When Playing Trustworthy Players in an Iterated Prisoner's Dilemma. *J. Neurosci.* **39**, 307–320 (2019).

10. Gabay, A. S., Radua, J., Kempton, M. J. & Mehta, M. A. The Ultimatum Game and the brain: A meta-analysis of neuroimaging studies. *Neurosci. Biobehav. Rev.* **47**, 549–558 (2014).

747   11. Güth, W., Schmittberger, R. & Schwarze, B. An experimental analysis of ultimatum bargaining. *J.*

748   *Econ. Behav. Organ.* **3**, 367–388 (1982).

749   12. King-Casas, B. *et al.* The Rupture and Repair of Cooperation in Borderline Personality Disorder.

750   *Science* **321**, 806–810 (2008).

751   13. Oosterbeek, H., Sloof, R. & Kuilen, G. van de. Cultural Differences in Ultimatum Game

752   Experiments: Evidence from a Meta-Analysis. *Exp. Econ.* **7**, 171–188 (2003).

753   14. Raihani Nichola J. & Barclay Pat. Exploring the trade-off between quality and fairness in human

754   partner choice. *R. Soc. Open Sci.* **3**, 160510 (2016).

755   15. Rilling, J. K. & Sanfey, A. G. The Neuroscience of Social Decision-Making. *Annu. Rev. Psychol.* **62**,

756   23–48 (2011).

757   16. Camerer, C. F. Progress in behavioral game theory. *J. Econ. Perspect.* **11**, 167–188 (1997).

758   17. Mastroianni, A. M., Gilbert, D. T., Cooney, G. & Wilson, T. D. Do conversations end when people

759   want them to? *Proc. Natl. Acad. Sci.* **118**, e2011809118 (2021).

760   18. Sommerfeld, R. D., Krambeck, H.-J., Semmann, D. & Milinski, M. Gossip as an alternative for direct

761   observation in games of indirect reciprocity. *Proc. Natl. Acad. Sci.* **104**, 17435–17440 (2007).

762   19. Dunbar, R. I., Marriott, A. & Duncan, N. D. Human conversational behavior. *Hum. Nat.* **8**, 231–246

763   (1997).

764   20. Schroeder, J. Ending Conversation is a Fraught Endeavor. *Trends Cogn. Sci.* **25**, 552–553 (2021).

765   21. Charnov, E. L. Optimal foraging, the marginal value theorem. *Theor. Popul. Biol.* **9**, 129–136 (1976).

766   22. Mobbs, D., Trimmer, P. C., Blumstein, D. T. & Dayan, P. Foraging for foundations in decision

767   neuroscience: insights from ethology. *Nat. Rev. Neurosci.* **19**, 419 (2018).

768   23. Becker, S. W., Ronen, J. & Sorter, G. H. Opportunity Costs-An Experimental Approach. *J. Account.*

769   *Res.* **12**, 317–329 (1974).

770   24. Niv, Y., Daw, N. D., Joel, D. & Dayan, P. Tonic dopamine: opportunity costs and the control of

771   response vigor. *Psychopharmacology (Berl.)* **191**, 507–520 (2007).

772   25. Kurzban, R., Duckworth, A., Kable, J. W. & Myers, J. An opportunity cost model of subjective effort

773   and task performance. *Behav. Brain Sci.* **36**, 661–679 (2013).

774   26. Constantino, S. & Daw, N. D. Learning the opportunity cost of time in a patch-foraging task. *Cogn.*

775   *Affect. Behav. Neurosci.* **15**, 837–853 (2015).

776   27. Le Heron, C. *et al.* Dopamine Modulates Dynamic Decision-Making during Foraging. *J. Neurosci.*

777   **40**, 5273–5282 (2020).

778   28. Gabay, A. S. & Apps, M. A. J. Foraging optimally in social neuroscience: computations and

779   methodological considerations. *Soc. Cogn. Affect. Neurosci.* (2020) doi:10.1093/scan/nsaa037.

780   29. Yoo, S. B. M., Hayden, B. Y. & Pearson, J. M. Continuous decisions. *Philos. Trans. R. Soc. B* **376**,

781   20190664 (2021).

782   30. Stephens, D. W. & Krebs, J. R. *Foraging Theory*. (Princeton University Press, 1986).

783   31. Cassini, M. H., Lichtenstein, G., Ongay, J. P. & Kacelnik, A. Foraging behaviour in guinea pigs:

784   further tests of the marginal value theorem. *Behav. Processes* **29**, 99–112 (1993).

785   32. Krebs, J. R., Ryan, J. C. & Charnov, E. L. Hunting by expectation or optimal foraging? A study of

786   patch use by chickadees. *Anim. Behav.* **22**, 953-IN3 (1974).

787   33. Lewis, A. R. Selection of Nuts by Gray Squirrels and Optimal Foraging Theory. *Am. Midl. Nat.* **107**,

788   250–257 (1982).

789   34. Hassell, M. P. & Southwood, T. R. E. Foraging Strategies of Insects. *Annu. Rev. Ecol. Syst.* **9**, 75–98

790   (1978).

791   35. Hayden, B. Y., Pearson, J. M. & Platt, M. L. Neuronal basis of sequential foraging decisions in a

792   patchy environment. *Nat. Neurosci.* **14**, 933–939 (2011).

793   36. Garrett, N. & Daw, N. D. Biased belief updating and suboptimal choice in foraging decisions. *Nat.*

794   *Commun.* **11**, 3417 (2020).

795   37. Yoon, T., Geary, R. B., Ahmed, A. A. & Shadmehr, R. Control of movement vigor and decision

796   making during foraging. *Proc. Natl. Acad. Sci.* **115**, E10476–E10485 (2018).

797   38. Goldfarb, A. & Prince, J. Internet adoption and usage patterns are different: Implications for the

798   digital divide. *Inf. Econ. Policy* **20**, 2–15 (2008).

799   39. Lindström, B. *et al.* A computational reward learning account of social media engagement. *Nat.*

800   *Commun.* **12**, 1311 (2021).

801   40. Davidson, J. D. & Hady, A. E. Foraging as an evidence accumulation process. *PLOS Comput. Biol.*

802   **15**, e1007060 (2019).

803   41. Kilpatrick, Z. P., Davidson, J. D. & Hady, A. E. Normative theory of patch foraging decisions.

804   *ArXiv200410671 Math Q-Bio* (2020).

805   42. Santini, Z. I., Koyanagi, A., Tyrovolas, S., Mason, C. & Haro, J. M. The association between social

806   relationships and depression: A systematic review. *J. Affect. Disord.* **175**, 53–65 (2015).

807   43. Hirschfeld, R. M. *et al.* Social functioning in depression: a review. *J. Clin. Psychiatry* **61**, 268–275

808   (2000).

809   44. Bangee, M., Harris, R. A., Bridges, N., Rotenberg, K. J. & Qualter, P. Loneliness and attention to

810   social threat in young adults: Findings from an eye tracker study. *Personal. Individ. Differ.* **63**, 16–

811   23 (2014).

812   45. Schinka, K. C., van Dulmen, M. H., Mata, A. D., Bossarte, R. & Swahn, M. Psychosocial predictors

813   and outcomes of loneliness trajectories from childhood to early adolescence. *J. Adolesc.* **36**, 1251–

814   1260 (2013).

815   46. Cacioppo, S. *et al.* Loneliness and implicit attention to social threat: A high-performance electrical

816   neuroimaging study. *Cogn. Neurosci.* **7**, 138–159 (2016).

817   47. Stek, M. L. *et al.* Is Depression in Old Age Fatal Only When People Feel Lonely? *Am. J. Psychiatry*

818   **162**, 178–180 (2005).

819   48. Matthews, T. *et al.* Loneliness and neighborhood characteristics: A multi-informant, nationally

820   representative study of young adults. *Psychol. Sci.* **30**, 765–775 (2019).

821   49. Engel, C. Dictator games: a meta study. *Exp. Econ.* **14**, 583–610 (2011).

822   50. Henrich, J. *et al.* 'Economic man' in cross-cultural perspective: behavioral experiments in 15 small-
823   scale societies. *Behav. Brain Sci.* **28**, 795–815; discussion 815-855 (2005).

824   51. Kahneman, D., Knetsch, J. L. & Thaler, R. H. Fairness and the Assumptions of Economics. *J. Bus.*
825   **59**, S285–S300 (1986).

826   52. *The Handbook of Experimental Economics*. (1997).

827   53. Chaudhuri, A. Sustaining cooperation in laboratory public goods experiments: a selective survey
828   of the literature. *Exp. Econ.* **14**, 47–83 (2011).

829   54. Charnov, E. L. OPTIMAL FORAGING, MARGINAL VALUE THEOREM. *Theor. Popul. Biol.* **9**, 129–136
830   (1976).

831   55. Bernstein, C., Kacelnik, A. & Krebs, J. R. INDIVIDUAL DECISIONS AND THE DISTRIBUTION OF
832   PREDATORS IN A PATCHY ENVIRONMENT .2. THE INFLUENCE OF TRAVEL COSTS AND STRUCTURE
833   OF THE ENVIRONMENT. *J. Anim. Ecol.* **60**, 205–225 (1991).

834   56. Chong, T. T.-J. *et al.* Neurocomputational mechanisms underlying subjective valuation of effort
835   costs. *PLoS Biol.* **15**, e1002598 (2017).

836   57. Contreras-Huerta, L. S., Pisauro, A. & Apps, M. A. Effort shapes social cognition and behaviour: A
837   neuro-cognitive framework. *Neurosci. Biobehav. Rev.* (2020).

838   58. Lockwood, P. L. *et al.* Prosocial apathy for helping others when effort is required. *Nat. Hum. Behav.*
839   **1**, s41562-017–0131 (2017).

840   59. De Jong Gierveld, J. & Van Tilburg, T. The De Jong Gierveld short scales for emotional and social
841   loneliness: tested on data from 7 countries in the UN generations and gender surveys. *Eur. J.*
842   *Ageing* **7**, 121–130 (2010).

843   60. Turrin, C., Fagan, N. A., Monte, O. D. & Chang, S. W. C. Social resource foraging is guided by the
844   principles of the Marginal Value Theorem. *Sci. Rep.* **7**, 11274 (2017).

845   61. Hunter, L. E. & Daw, N. D. Context-sensitive valuation and learning. *Curr. Opin. Behav. Sci.* **41**, 122–
846   127 (2021).

847   62. Hayden, B. & Niv, Y. The case against economic values in the orbitofrontal cortex (or anywhere

848   else in the brain). (2020) doi:10.31234/osf.io/7hgup.

849   63. Krajbich, I., Hare, T., Bartling, B., Morishima, Y. & Fehr, E. A common mechanism underlying food

850   choice and social decisions. *PLoS Comput. Biol.* **11**, e1004371 (2015).

851   64. Gold, J. I. & Shadlen, M. N. The neural basis of decision making. *Annu Rev Neurosci* **30**, 535–574

852   (2007).

853   65. Mante, V., Sussillo, D., Shenoy, K. V. & Newsome, W. T. Context-dependent computation by

854   recurrent dynamics in prefrontal cortex. *Nature* **503**, 78–84 (2013).

855   66. Hutcherson, C. A., Bushong, B. & Rangel, A. A Neurocomputational Model of Altruistic Choice and

856   Its Implications. *Neuron* **87**, 451–462 (2015).

857   67. Apps, M. A., McKay, R., Azevedo, R. T., Whitehouse, H. & Tsakiris, M. Not on my team: Medial

858   prefrontal cortex responses to ingroup fusion and unfair monetary divisions. *Brain Behav.* **8**,

859   e01030 (2018).

860   68. Wright, N. D., Symmonds, M., Fleming, S. M. & Dolan, R. J. Neural segregation of objective and

861   contextual aspects of fairness. *J. Neurosci. Off. J. Soc. Neurosci.* **31**, 5244–5252 (2011).

862   69. Andersen, S., Ertaç, S., Gneezy, U., Hoffman, M. & List, J. A. Stakes Matter in Ultimatum Games.

863   *Am. Econ. Rev.* **101**, 3427–3439 (2011).

864   70. Harman, G. What is moral relativism? in *Values and morals* 143–161 (Springer, 1978).

865   71. Harman, G. & Thomson, J. J. Moral relativism and moral objectivity. (1996).

866   72. Mastroianni, A. M., Gilbert, D. T., Cooney, G. & Wilson, T. D. Do conversations end when people

867   want them to? *Proc. Natl. Acad. Sci.* **118**, (2021).

868   73. Bächinger, M. *et al.* Human motor fatigability as evoked by repetitive movements results from a

869   gradual breakdown of surround inhibition. *Elife* **8**, e46750 (2019).

870   74. Contreras-Huerta, L. S., Lockwood, P. L., Bird, G., Apps, M. A. & Crockett, M. J. Prosocial behavior

871   is associated with transdiagnostic markers of affective sensitivity in multiple domains. *Emotion*

872   (2020).

873   75. Peirce, J. *et al.* PsychoPy2: Experiments in behavior made easy. *Behav. Res. Methods* **51**, 195–203

874   (2019).

875   76. R Development Core Team. *R: A language and environment for statistical computing*. (R

876   Foundation for Statistical Computing, 2020).

877   77. Bates, D., Mächler, M., Bolker, B. & Walker, S. Fitting Linear Mixed-Effects Models Using lme4. *J.*

878   *Stat. Softw.* **67**, 1–48 (2015).

879   78. Kuznetsova, A., Brockhoff, P. B. & Christensen, R. H. B. lmerTest Package: Tests in Linear Mixed

880   Effects models. *J. Stat. Softw.* **82**, 1–26 (2017).

881   79. Lenth, R. V. *emmeans: Estimated Marginal Means*. (2020).

882   80. Fox, J. & Weisberg, S. *An {R} Companion to Applied Regression*. (Sage).

883   81. Long, J. A. *interactions: Comprehensive, User-Friendly Toolkit for Probing Interactions*. (2019).

884   82. Wickham, H. *ggplot2: Elegant Graphics for Data Analysis*. (Springer-Verlag, 2016).

885   doi:10.1007/978-0-387-98141-3.

886   83. Ratcliff, R., Smith, P. L., Brown, S. D. & McKoon, G. Diffusion Decision Model: Current Issues and

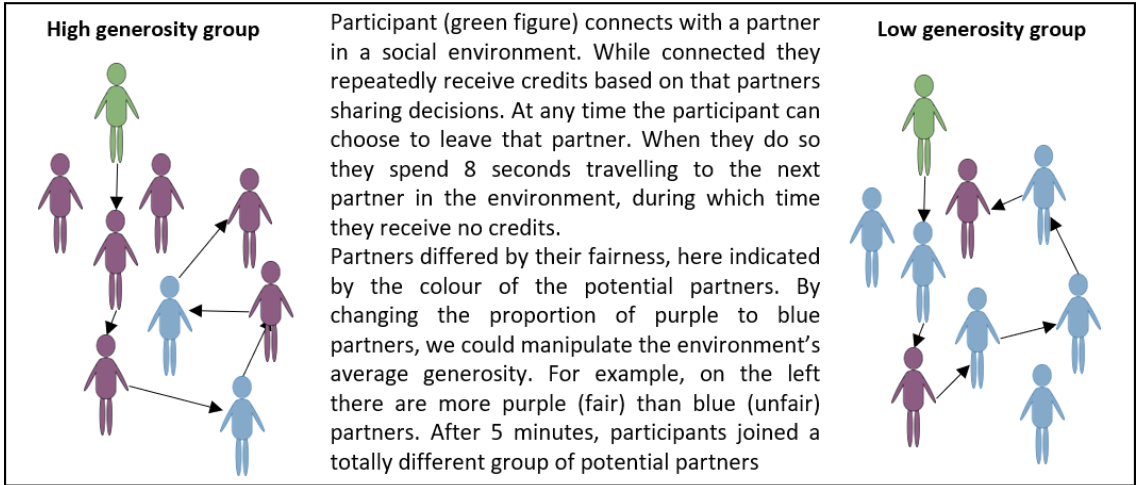887   History. *Trends Cogn. Sci.* **20**, 260–281 (2016).
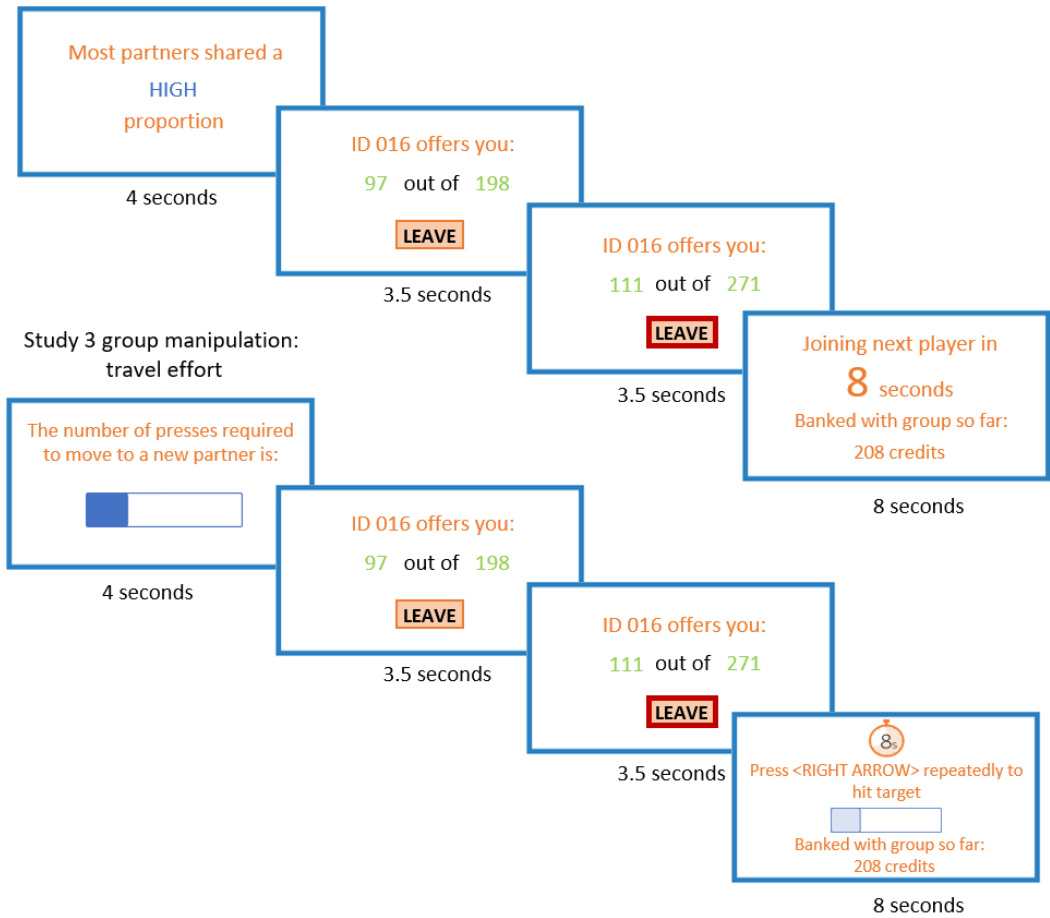
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Supplementary materials

Supplementary methods

Experimental paradigm

Supplementary Figure 1: Top: Diagrammatic representation of the task as explained to participants. Bottom: Task structure for Studies 1 – 3. For Studies 1 &2 the environment manipulation was average generosity. For Study 3 it was effort required to move between partners

898

899 *Supplementary Table 1: Demographics by study, after exclusions.*

	Study 1	Study 2	Study 3	Study 4
N	19	25	24	81
%F	76.4	65.4	73.1	49.4
Age	27.6 (SD 5.3)	23.7 (SD 4.5)	24.2 (SD 5.0)	30.7 (SD 8.5)
Environment manipulation	Generosity	Generosity	Effort	Generosity

900

901

902 # Supplementary results

903 ## Behavioural analyses

904 *Control analysis (Study 1 & 2) – excluding zero fairness trials*

905 The fairness trajectories used in Study 1 and Study 2 (see methods for details) allowed for fairness to
906 drop to zero. Continuing to interact with a partner while they share no money is a legitimate behaviour
907 in the task, but it could also be a sign of inattention. We repeated the analyses from both study 1 and
908 study 2, excluding decisions made after the fairness had dropped to zero. The main effects of partner
909 and environment type remained statistically significant for both studies, while the interaction
910 between predictors was non-significant for both studies (Supplementary Table 1).

911 *Supplementary Table 2: Results from linear mixed models for Study 1 & Study 2 when excluding decisions when fairness was*
912 *equal to zero*

Study	Predictor	b	SE	t	*p-value*	X^2	*p-value*
1	Partner	-8.21	0.77	-10.619	< 0.001	113.36	< 0.001
	Environment	2.53	0.78	3.237	0.001	11.01	0.001
	Partner*environment interaction	-2.00	1.54	-1.297	0.195	1.68	0.195
2	Partner	-10.15	1.21	-8.400	< 0.001	70.98	< 0.001
	Environment	2.52	1.13	2.221	0.044	4.87	0.027
	Partner*environment interaction	1.03	1.56	0.658	0.51	0.43	0.510

913

914

Supplementary analysis – fairness at leaving

916 We examined whether the fairness at the time of choosing to leave a partner differed by partner type
917 or social environment for each study. Across all studies there was a main effect of both partner type
918 and social environment, and no interaction. In all cases, the fairness at leaving was lower for less fair
919 partners than fairer partners, and in low quality environments compared to high.

920 *Supplementary Table 3: Results from linear mixed models for all studies, with fairness as the outcome variable*

Study	Predictor	b	SE	t	p-value	X^2	p-value
1	Partner	-2.63	0.63	-4.146	0.001	16.82	< 0.001
	Environment	-2.08	0.90	-2.316	0.032	5.48	0.019
	Partner*environment interaction	1.46	0.94	1.56	0.120	2.42	0.120
2	Partner	-3.15	0.75	-4.170	< 0.001	17.40	< 0.001
	Environment	-2.68	0.92	2.914	0.008	8.51	0.004
	Partner*environment interaction	-0.58	0.99	-0.588	0.557	0.35	0.557
3	Partner	-1.99	0.37	-5.311	< 0.001	27.95	< 0.001
	Environment	-1.23	0.38	-3.268	0.001	10.48	0.001
	Partner*environment interaction	-0.40	0.75	-0.537	0.591	0.29	0.591
4	Decay rate (partner type)	0.02	0.001	10.877	< 0.001	120.33	< 0.001
	Environment	-0.01	0.004	-2.142	0.035	4.54	0.033
	Partner*environment interaction	-0.004	0.002	-1.724	0.085	2.97	0.085

921

922

923 *Supplementary analysis – earnings*

924 We examined whether the amount earned per partner differed by partner type or social environment
925 for each study. Across all studies there was a main effect of both partner type and social environment.
926 In all cases, participants earned less with unfair partners than fairer partners, and earned more in low
927 quality environments than high quality environments. Since participants accumulate reward while
928 interacting with a partner, and earn no reward while travelling between partners, this pattern of
929 results is to be expected. Leaving times were earlier in a high opportunity cost environment, meaning
930 more time was spent travelling, and therefore less reward earned. People spent more time interacting
931 with fair partners than unfair partners, and therefore earned more money with those partners. There
932 was a partner by environment interaction in Study 1, but this did not replicate across studies.

933 *Supplementary Table 4: Results from linear mixed models for all studies, with earnings as the outcome variable*

| Study	Predictor	b	SE	t	*p-value*	X^2	*p-value*
1	Partner	-343.28	40.68	-8.44	0.001	71.84	< 0.001
	Environment	72.42	32.11	2.255	0.037	5.23	0.022
	Partner*environment interaction	-71.00	29.94	-2.371	0.018	5.62	0.018
2	Partner	-331.19	36.38	-9.103	< 0.001	82.86	< 0.001
	Environment	78.98	29.58	2.670	0.14	7.11	0.008
	Partner*environment interaction	-13.99	30.87	-0.453	0.651	0.21	0.650
3	Partner	-214.50	33.59	-6.385	< 0.001	41.51	< 0.001
	Environment	145.77	33.63	4.334	< 0.011	18.50	< 0.001
	Partner*environment interaction	40.72	67.05	0.607	0.544	0.37	0.544
4	Decay rate (partner type)	758.15	60.79	12.472	< 0.001	156.44	< 0.001
	Environment	324.72	106.27	3.056	0.003	9.38	0.002
	Partner*environment interaction	-51.24	55.59	-0.922	0.357	0.85	0.357

934

935 *Supplementary analysis – do depression/loneliness scores predict earnings?*

936 To test whether the altered behaviour seen in participants with higher self-reported depression and
937 loneliness was more economically rational, we carried out two regression analyses predicting overall
938 earnings by depression or loneliness. Supplementary Table 5 shows that neither of these predictors
939 were significant.

940 *Supplementary Table 5: Results from regression analyses testing the relationship between overall task earnings and*
941 *depression/loneliness*

Predictor	b	SE	t	*p-value*
Depression	1069	3307	77.229	0.749
Loneliness	225.5	1805.9	0.125	0.901

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944   Drift diffusion model results

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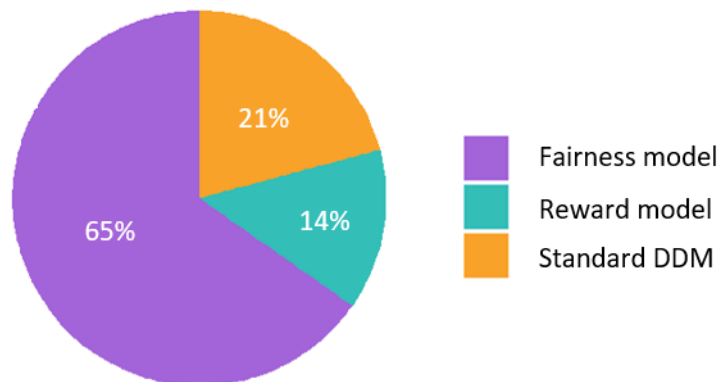
947   *Supplementary Figure 2: Percentage of participants with each model as their winning model. The fairness adapted DDM was*
948   *the best fitting model in 65% of participants*

949

950   *Mixed effect models on the non-winning modelled-simulated data*

951   To further demonstrate that the reward model and standard DDM did not capture the shape of the
952   experimental data we ran the statistical model on the simulated dataset from these models.
953   Supplementary Table 4 shows how neither model captures both the partner-type and social
954   environment effect present in the real data.

955   *Supplementary Table 6: mixed model results for simulated data from non-winning DDMs*

Model	Predictor	b	SE	t	p-value	X^2	p-value
Reward	Partner	0.002	.014	0.012	0.990	0.46	0.495
	Environment	-3.07	0.14	-21.705	<0.001	975.86	<0.001
	Partner*environment interaction	-0.1	0.20	-0.694	0.488	0.48	0.488
Standard DDM	Partner	0.05	0.14	0.383	0.702	1.09	0.297
	Environment	-0.07	0.14	-0.575	0.565	0.10	0.751
	Partner*environment interaction	0.10	.019	0.496	0.620	0.25	0.620

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957   *Fitted parameter values from winning DDM*

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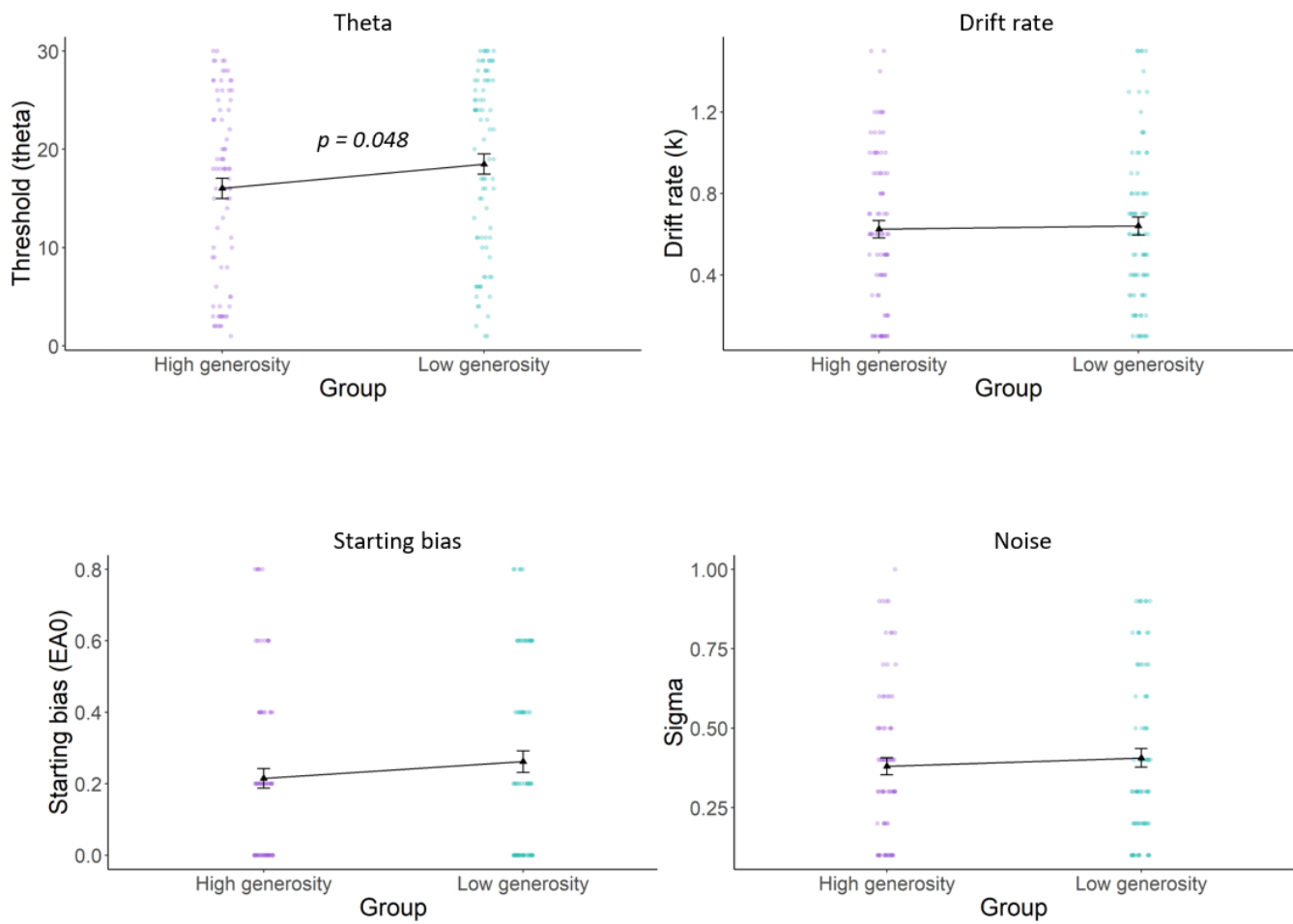
959   *Supplementary Figure 3: fitted parameter values for the winning Fairness DDM. The threshold parameter, theta differed*
960   *across environments. All other parameters did not differ significantly between social environments*

961

962

963