# Developmental asymmetries in learning to adjust to cooperative and uncooperative environments

Bianca Westhoff[1,2], Lucas Molleman[3,4], Essi Viding[5], Wouter van den Bos[3,4,6] & Anna C. K. van Duijvenvoorde[1,2]

[1] Institute of Psychology, Leiden University, Leiden, the Netherlands

[2] Leiden Institute for Brain and Cognition, Leiden, the Netherlands

[3] Department of Psychology, University of Amsterdam, Amsterdam, the Netherlands

[4] Amsterdam Brain and Cognition, University of Amsterdam, Amsterdam, the Netherlands

[5] Division of Psychology and Language Sciences, University College London, United Kingdom

[6] Center for Adaptive Rationality, Max Planck Institute for Human Development, Berlin, Germany

**Corresponding author**

Bianca Westhoff, e-mail: b.westhoff@fsw.leidenuniv.nl

# 1 Abstract

2 Learning to successfully navigate social environments is a critical developmental goal, predictive of

3 long-term wellbeing. However, little is known about how people learn to adjust to different social

4 environments, and how this behaviour emerges across development. Here, we use a series of

5 economic games to assess how children, adolescents, and young adults learn to adjust to social

6 environments that differ in their level of cooperation (i.e., trust and coordination). Our results show

7 an asymmetric developmental pattern: adjustment requiring uncooperative behaviour remains

8 constant across adolescence, but adjustment requiring cooperative behaviour improves markedly

9 across adolescence. Behavioural and computational analyses reveal that age-related differences in

10 this social learning are shaped by age-related differences in the degree of inequality aversion and in

11 the updating of beliefs about others. Our findings point to early adolescence as a phase of rapid

12 change in cooperative behaviours, and highlight this as a key developmental window for

13 interventions promoting well-adjusted social behaviour.

## Introduction

14

15    Humans have evolved in a highly social environment in which they continuously make decisions

16    about how to engage with others. Well-adjusted social behaviour requires individuals to learn whom

17    they can trust and cooperate with. We typically trust others whom we expect to reciprocate that

18    trust in the future and beliefs about others' trustworthiness are updated through everyday

19    experiences. For example, if a friend violates our trust, this calls for an adjustment of our belief in

20    their trustworthiness. This may not happen on the first violation, but if this friend continues their

21    untrustworthy behaviour, the friendship is unlikely to survive. Adjusting our beliefs based on

22    outcomes of social interactions enables decision making that matches the situation and can be

23    critical for successful navigation of the social world. In line with this notion, well-adjusted social

24    behaviour has been linked to positive developmental trajectories (e.g., in health, education, and

25    social development), and is important for long-term mental health [1–4]. With the rise of complex

26    social worlds (both online and offline), learning about and adjusting to different social environments

27    may be more important than ever. Yet little is known about the factors that underlie learning and

28    adjusting in social environments, and how these skills manifest across adolescence.

29         Mounting evidence suggests that adolescence – the period between childhood and young

30    adulthood – is a life phase in which learning and flexible behaviour mature rapidly (see e.g., [1,3,5,6]).

31    Moreover, adolescence is marked by a social reorientation: individuals start to form larger peer

32    groups, peers gain in importance compared with parents, and social interactions become more

33    complex [7–10]. Adolescence is, therefore, an important life phase for developing well-adjusted social

34    behaviour, with cooperative and uncooperative behaviours becoming more salient as adolescents

35    deal with their social environments more independently. Developmental research into social

36    decision-making has shown that from an early age, children trust others and recognize that investing

37    in others can lead to mutual benefits [11]. Cooperative behaviours, such as trust and prosocial

38    behaviour, are thought to continuously increase during adolescence [5,12–14] (but see [15]). A more

39    nuanced view is that adolescents do not show more cooperative behaviours per se, but instead

40    increasingly tailor their behaviour to the social environment. For example, when undertaking

41    prosocial actions they increasingly differentiate between friends and strangers[16–18]. Also, adolescents

42    learn to adjust to interaction partners that differ in their level of trustworthiness [19], something that

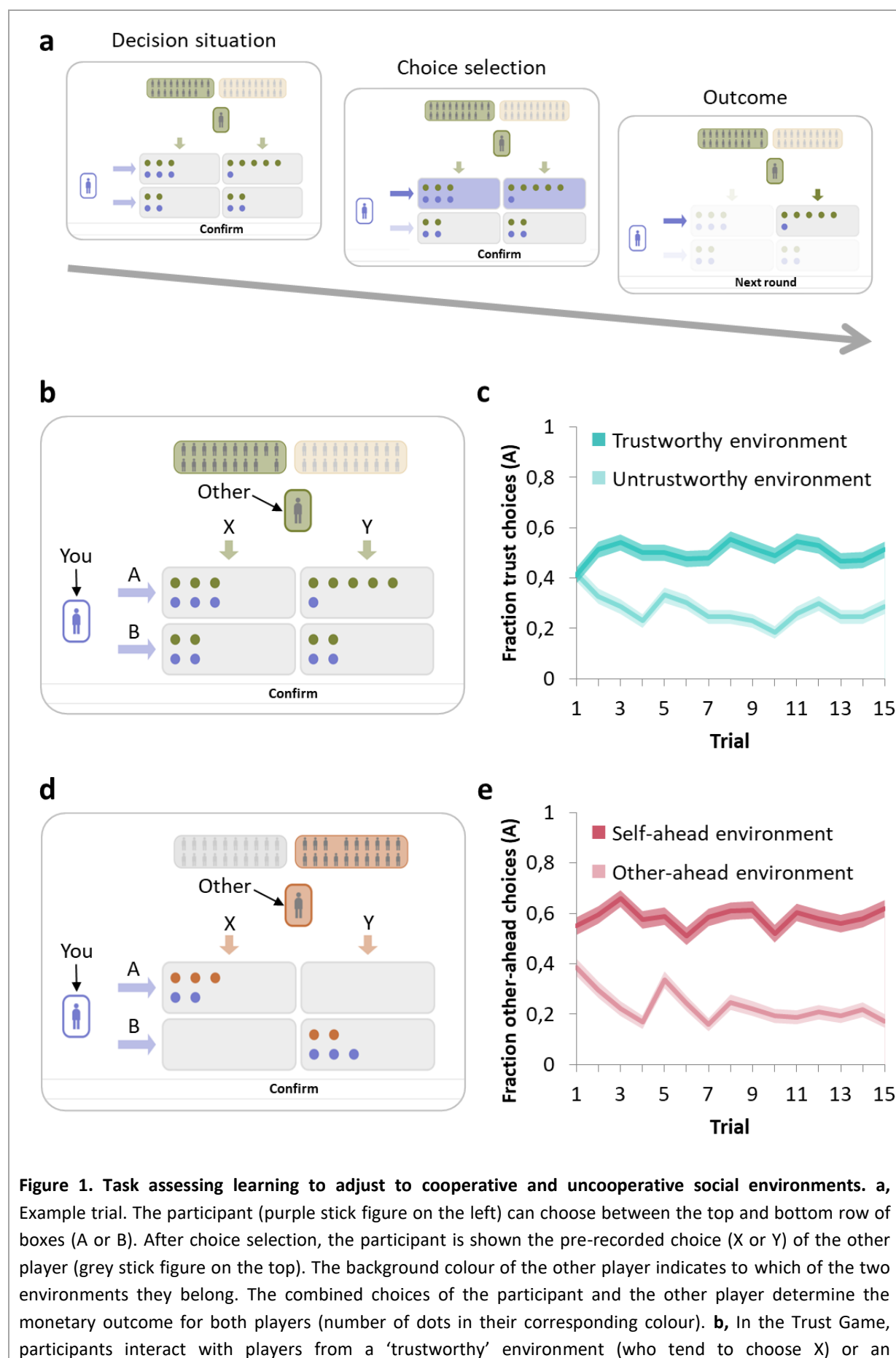43    children find difficult [11].

44         Theoretically, decisions to cooperate can be based on at least three distinctive factors, each

45    of which could differ between individuals and could contribute to developmental differences in

46    adjusting behaviour in social contexts: (1) social preferences, (2) prior expectations, and (3) updating

47    of expectations. First, *social preferences* refer to individuals caring about relative outcomes, i.e.

2

48   disliking having either a better or worse outcome than others [20]. Across childhood, there is a

49   decrease in the preference of avoiding getting less than others (i.e., disadvantageous inequality

50   aversion) and an increase in the preference of avoiding getting *more* than others (i.e., advantageous

51   inequality aversion [21]; and see [22] for a review). Although evidence suggests that social preferences

52   continue to develop across adolescence (e.g., [23]), little is known about how they impact learning in

53   social environments. For instance, high levels of disadvantageous inequality aversion could prevent

54   cooperative behaviour due to a fear of getting less than others, even if there is a relatively strong

55   expectation that others will cooperate.

56        Second, *prior expectations* (i.e., descriptive norms, the perceptions of what most people do;

57   [24–26]) inform decision-making by generating predictions about the behaviour of others (e.g., I will

58   cooperate if this person is likely to reciprocate). Individual differences in initial expectations about

59   others may lead to individual differences in choices [27], and it is conceivable that different age groups

60   have varying prior expectations. However, prior expectations have hardly been studied in

61   developmental populations, despite being important determinants of cooperative behaviours.

62        Third, adjusting behaviour requires expectations to be *updated* in response to new

63   information. Updating of expectations in social environments can be captured by reinforcement

64   learning (RL) models (e.g., [28–30]), in which learning is driven by differences between expected and

65   received rewards (i.e., prediction errors). Adolescence is characterized by substantial improvements

66   in flexible learning and quick adaptation to novel non-social contexts ([31–33]); whether this extends to

67   the social domain, however, is still unclear (but see [34]).

68        Here we examine experimentally how children, adolescents, and adults adjust to social

69   environments that differ in their level of cooperation, and aim to provide a mechanistic explanation

70   by evaluating the role of social preferences, prior expectations, and expectation updating. To

71   achieve this goal, we deployed a set of economic games, together with behavioural analyses and

72   computational reinforcement learning modelling. Our cross-sectional sample spanned from late

73   childhood into early adulthood (8 to 23 years old, *N*=244). Participants played age-appropriate

74   versions of two well-studied incentivized economic games: A Trust Game (Figure 1b) and a

75   Coordination Game (Figure 1d). These two games involve key types of cooperative behaviours: trust

76   and coordination. Trust is key for mutually beneficial cooperation to be initiated and sustained (e.g.,

77   [12,19,35]), and for achieving beneficial outcomes for all interaction partners involved. Yet, trust also

78   creates a hazard of being betrayed. Similarly, coordinating one's behaviour with others is often

79   critical for collective welfare, even though outcomes may not always equally benefit all interaction

80   partners [36,37].

**Figure 1. Task assessing learning to adjust to cooperative and uncooperative social environments. a,** Example trial. The participant (purple stick figure on the left) can choose between the top and bottom row of boxes (A or B). After choice selection, the participant is shown the pre-recorded choice (X or Y) of the other player (grey stick figure on the top). The background colour of the other player indicates to which of the two environments they belong. The combined choices of the participant and the other player determine the monetary outcome for both players (number of dots in their corresponding colour). **b,** In the Trust Game, participants interact with players from a 'trustworthy' environment (who tend to choose X) or an

'untrustworthy' environment (who tend to choose Y). Participants' own monetary payoffs are maximized by choosing to trust (choose A) a player from a trustworthy environment, and to withhold trust (choose B) from a player from the untrustworthy environment. In this trust-game setup only disadvantageous inequality aversion may play a role in decision making **c,** Participant choices over trials per social environment, pooled across all participants. Over the course of the game, participants adjusted their choices by directing their trust towards players from the trustworthy environment, and away from players from the untrustworthy environment (N=244). **d,** In the Coordination Game, participants' monetary payoffs are also maximised by matching the choices of their co-players. Again, social environments differ in their prevalence of (non)cooperation, reflected by players' tendencies to choose either X or Y. Coordinating on either of the outcomes (A,X) or (B,Y) will lead to positive outcomes. Respectively, participants' own monetary payoffs are maximized by choosing to put themselves behind (choose A) when confronted with a player from the self-ahead environment, and to put themselves ahead (choose B) when confronted with a player from the other-ahead environment. In this game both advantageous and disadvantageous inequality aversion may play a role in social decision-making. **e,** Participant choices over trials per social environment, pooled across all participants. Overall, participants learned to coordinate with players from both environments. (N=202). Shaded areas in panels c and e represent standard errors of the mean (s.e.m.).

The two games consisted of repeated one-shot interactions, in which both players had to choose between two options. In each trial, they encountered one new anonymous player from either a Cooperative environment or an Uncooperative environment. The decisions of these players had been recorded in a previous session with age-matched unfamiliar others (see *Methods, pre-test*). Participants were explained that between environments, players could differ in their tendency to choose X (see Figure 1b and 1d). To maximise their earnings, participants had to learn which environment was cooperative and which was uncooperative over the course of the game, and adjust their choices accordingly. The social environments in these games were probabilistic, as cooperative behaviours were displayed by 73% of the players in the cooperative environments, and by 27% of the players in the uncooperative environments.

Participants also played an iterative Ultimatum Game (UG) and Dictator Game (DG), which allowed us to estimate participants' social preferences (i.e., advantageous and disadvantageous inequality aversion; see *Methods*). We separately assessed participants' prior expectations of the behaviour of others before the start of the Trust Game and Coordination Game (see *Methods*). Furthermore, we used computational reinforcement-learning models [38] to model the updating of expectations between interactions. In these models, the learning rate quantifies how much an expectation violation modifies our subsequent expectations and consequently our decision-making. We allowed learning rates to decay over the course of the games because we expected that most of the learning about the environments would happen in the first set of trials. After that behaviour would stabilize, provided the environments did not change their behaviour (for more on learning rates and environmental stability see [39–41]). We extended these reinforcement learning models to

103     account for the measured prior expectations and social preferences [28], and compared the

104     parameters of these models across age cohorts (see *Methods*).
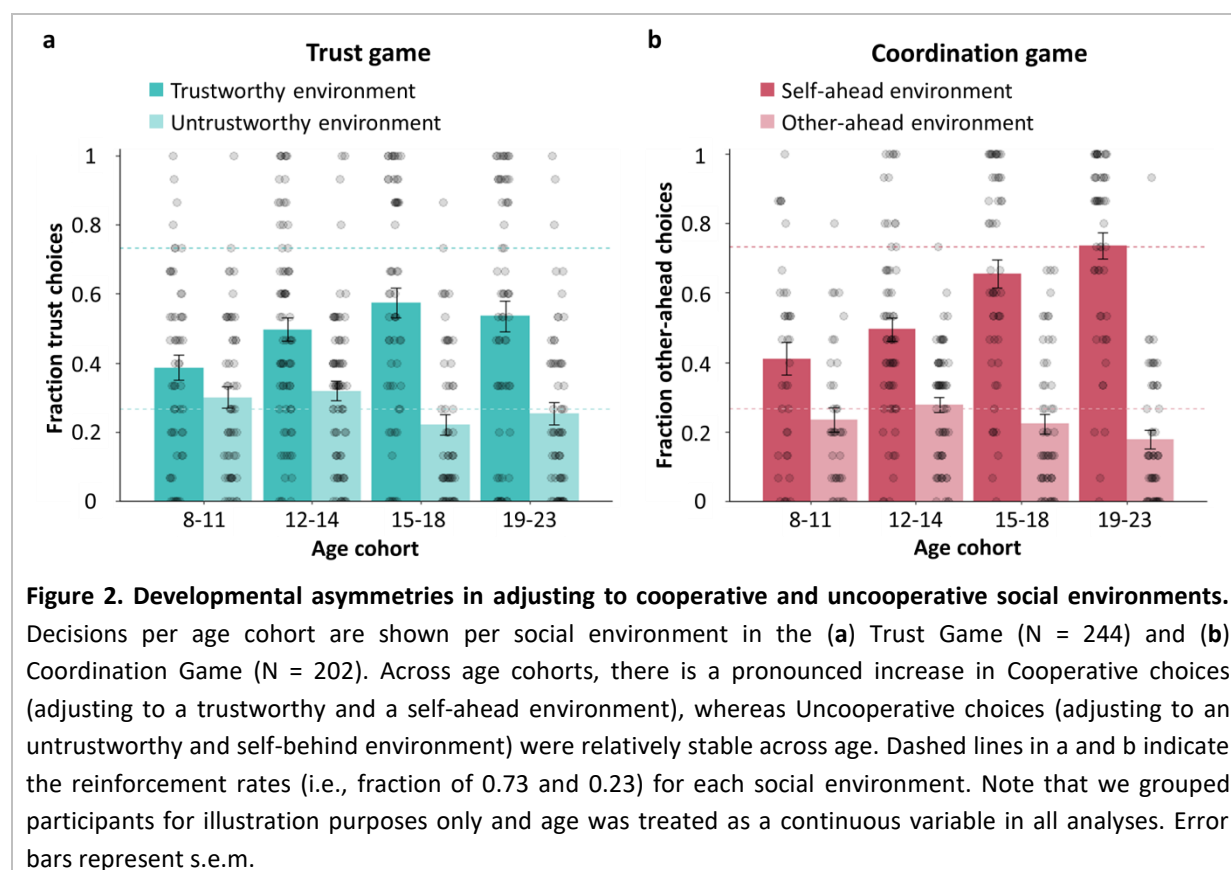
105     We hypothesized that participants would be able to learn to adjust their behaviours to social

106     environments differing in their level of (non)cooperation, but that across adolescence this ability

107     would improve rapidly. We expected that these developmental differences could be explained by a

108     combination of (1) social preferences (i.e., age-related changes in levels of advantageous and

109     disadvantageous inequality aversion), (2) prior expectations (i.e., age-related changes in

110     expectations about others' trustworthiness and tendencies to prioritise their own payoffs over those

111     of others) and (3) updating of expectations (i.e., age-related changes in learning rates).

112

## Results

114     **Learning to adjust to cooperative and uncooperative social environments across different ages**

115     First, we examined decisions over the course of the games to assess whether children, adolescents,

116     and young adults adjust their behaviour to different social environments with different levels of

117     cooperation. For this, we used the Trust Game in which participants maximized their monetary

118     outcomes by trusting trustworthy others and withhold trust from untrustworthy others (Figure 1b),

119     and the Coordination Game in which participants maximized their outcomes by coordinating with

120     the response of the others placing themselves ahead or behind. We performed a binomial

121     generalized linear mixed model (GLMM) per game on participants' binary choices, including social

122     preferences and prior estimations of others behaviour (see *Methods*).

123     For the Trust Game, results indicated an accelerated change in adolescence in which people

124     differentiated more between the trustworthy and untrustworthy environment (environment x age

125     linear, $B = -0.3$, $P < 0.001$; environment x age quadratic, $B = 0.207$, $P = 0.014$; N=244; see Table S1 for

126     full statistical analysis; Figure 2a). Post-hoc tests per social environment showed that trusting the

127     trustworthy others increased rapidly between ages 8-11 and 15-17 (age linear, $B = -0.374$, $P = 0.009$;

128     age quadratic, $B = 0.322$, $P = 0.018$). In contrast, adjusting to untrustworthy others improved slightly,

129     and monotonically across adolescence (age linear, $B = 0.229$, $P = 0.037$).

130

**Figure 2. Developmental asymmetries in adjusting to cooperative and uncooperative social environments.** Decisions per age cohort are shown per social environment in the (**a**) Trust Game (N = 244) and (**b**) Coordination Game (N = 202). Across age cohorts, there is a pronounced increase in Cooperative choices (adjusting to a trustworthy and a self-ahead environment), whereas Uncooperative choices (adjusting to an untrustworthy and self-behind environment) were relatively stable across age. Dashed lines in a and b indicate the reinforcement rates (i.e., fraction of 0.73 and 0.23) for each social environment. Note that we grouped participants for illustration purposes only and age was treated as a continuous variable in all analyses. Error bars represent s.e.m.
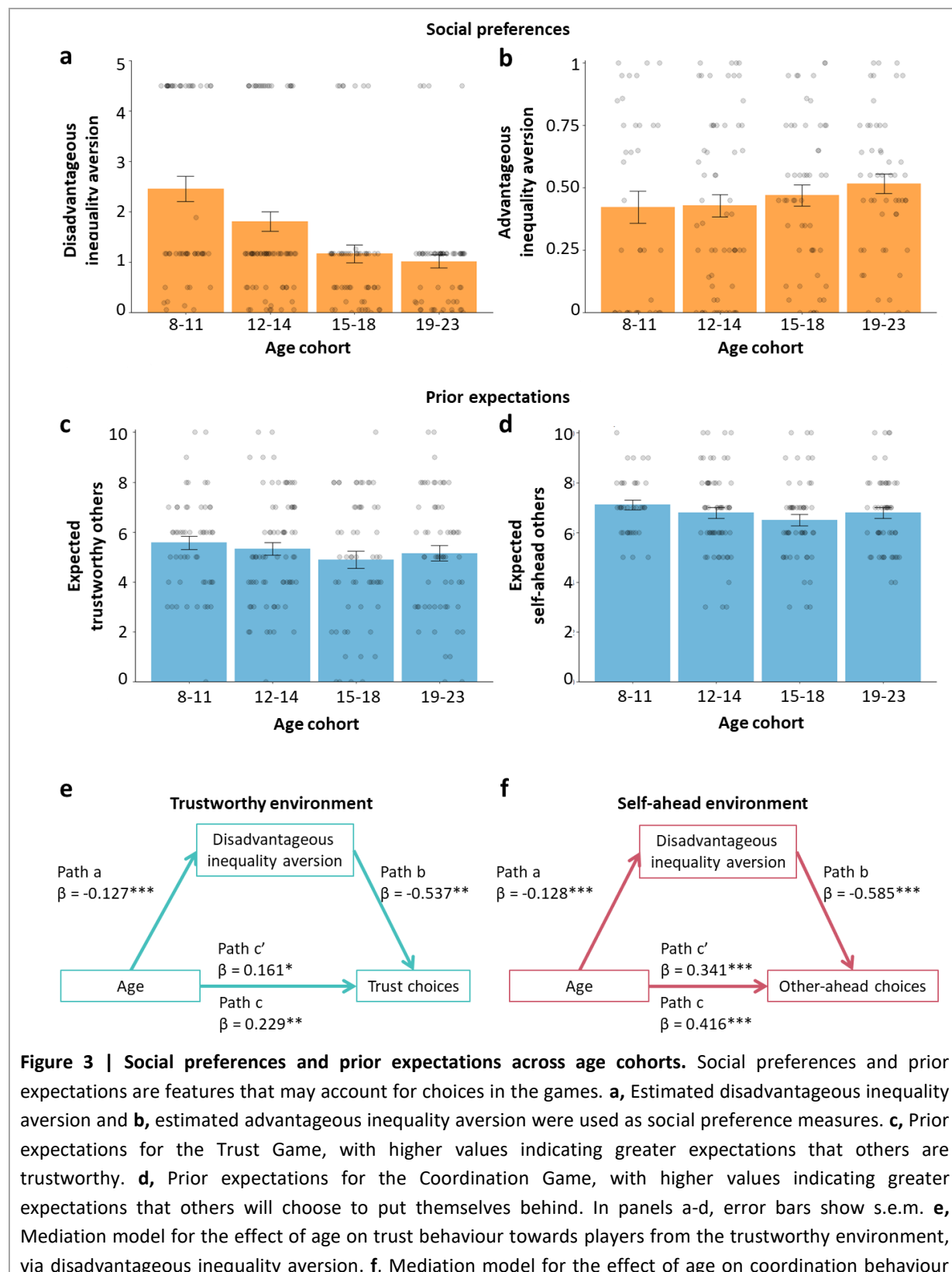
For the Coordination Game, results again indicated that with age, people differentiated more between the self-ahead and other-ahead environment (environment x age linear, $B = -0.446$, $P < 0.001$; N = 202; see Table S3 for full statistical analysis; Figure 2b). Post-hoc tests per social environment showed that optimally coordinating to the other-ahead environment (participant having fewer points than the other player) increased across adolescence (age linear, $B = -0.446$, $P < 0.001$). However, coordinating to the self-ahead environment (participant having more points than the other player) did not change with age; participants from all age cohorts adjusted quickly to this environment.

**Social preferences and prior expectations**

Social preferences (advantageous and disadvantageous inequality aversion) and prior expectations of others' behaviour are features that may account for age-related changes in learning to adjust to different social environments. Before further testing their relation to behaviour in the Trust Game and Coordination Game, we first examined the age-related changes in these parameters. Robust linear regression analyses (5000 bootstraps) indicated that only disadvantageous inequality aversion changed across age (Figure 3a-3d). Specifically, older participants were less averse to being behind than younger participants (age linear, B = -.127, $\beta = -0.324$, $P < 0.001$, 95% CI [-0.172, -0.083], N =

149     244). We did not observe significant age-related change for advantageous inequality aversion (age

150     linear, B = .01, β = 0.123, *P* = 0.071, 95% CI [-0.001, 0.021], N = 202), nor for prior expectations of

151     others' trustworthiness (age linear, *P* = 0.462; N = 245) or for prior expectations of others' tendency

152     to have more than the other (age linear, *P* = 0.478, N = 245).



**Figure 3 | Social preferences and prior expectations across age cohorts.** Social preferences and prior expectations are features that may account for choices in the games. **a,** Estimated disadvantageous inequality aversion and **b,** estimated advantageous inequality aversion were used as social preference measures. **c,** Prior expectations for the Trust Game, with higher values indicating greater expectations that others are trustworthy. **d,** Prior expectations for the Coordination Game, with higher values indicating greater expectations that others will choose to put themselves behind. In panels a-d, error bars show s.e.m. **e,** Mediation model for the effect of age on trust behaviour towards players from the trustworthy environment, via disadvantageous inequality aversion. **f,** Mediation model for the effect of age on coordination behaviour

towards players from the other-ahead environment, via disadvantageous inequality aversion. Note in mediation models: c = total effect, c' = direct effect; values are standardized regression coefficients of direct effects, and asterisks indicate significance levels (*$P < 0.05$, **$P < 0.01$, ***$P < 0.001$).
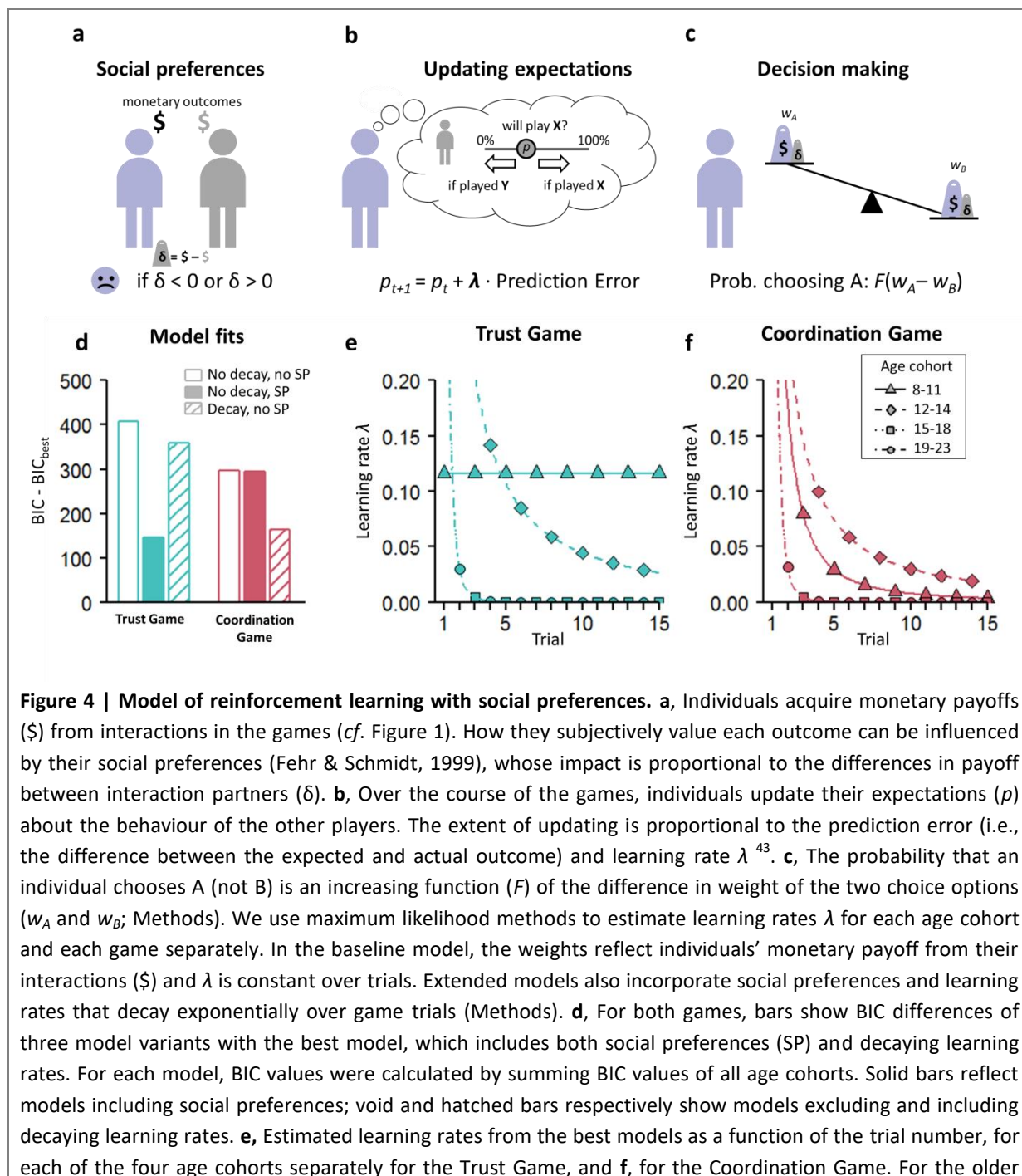
153

154     In a binomial GLMM analyses, advantageous and disadvantageous inequality aversion was

155     related to choices in the games (Tables S1 and S3). Greater disadvantageous inequality aversion was

156     associated with overall less trusting choices ($B = 0.194$, $P < 0.027$) and with less other-ahead choices

157     ($B = 0.184$, $P < 0.007$). In addition, greater advantageous inequality aversion was associated with

158     more other-ahead choices ($B = -0.162$, $P < 0.014$). In contrast, prior expectations were not related to

159     choices in both games.

160     To better understand what drives the age-related change in learning to adjust to the social

161     environments differing in their level of cooperation, we ran a mediation analysis per game.

162     Specifically, we examined whether the age-related changes in disadvantageous inequality aversion

163     explained the observed increase in cooperative behaviour across development controlling for

164     individual's level of uncooperative behaviour (Figure 3e; Figure 3f). We found that the improvement

165     across age in adjusting to the trustworthy environment ($\beta = 0.161$, $P = .040$) was partly explained by

166     the age-related decrease in disadvantageous inequality aversion (indirect effect = 0.068, $SE = 0.027$

167     CI [0.017, 0.125]). That is, older participants showed lower levels of disadvantageous inequality

168     aversion ($\beta = -0.127$, $P < 0.001$), which in turn resulted in more trust choices ($\beta = -0.537$, $P = 0.007$;

169     Figure 3e). This mediation analysis for the Coordination Game showed a similar effect of

170     disadvantageous inequality aversion partly explaining the age-related change in cooperative

171     behaviour. That is, older participants showed lower levels lower levels of disadvantageous inequality

172     aversion ($\beta = -0.128$, $P < 0.001$), which in turn resulted in less cooperative (other-ahead) choices ($\beta =$

173     $-0.585$, $P = < 0.001$; Figure 3f). Note that this partial mediation in the Coordination Game, did not

174     hold when advantageous inequality aversion was included as an additional mediator. This may relate

175     to the considerable reduction in sample size (N = 202 instead of N = 244) due to missing estimations

176     of individual's advantageous inequality aversion (see *Methods*).

177

178     **Computational modelling of updating expectations**

179     To understand how children, adolescents, and young adults update their expectations in different

180     social environments, we developed computational models that extend basic reinforcement learning

181     models [42]. In our models, participants use the outcome of interactions to update their expectations

182     of their interaction partners' choices in each social environment (Figure 4a-c). The extent to which

183     these expectations are updated is reflected in a learning rate ($\lambda$). Besides quantifying the updating of

184     expectations, this computational approach allows us to confirm the role of social preferences as

185 observed in our behavioural analyses. We extended the basic reinforcement model by i)

186 incorporating mean cohort-level social preferences to calculate a subjective value of interaction

187 monetary outcomes (Figure 4a, 4c) that drives decision making, and ii) by allowing learning rates

188 (expectation updating) to exponentially decay over trials of the game. Thus, we fitted four variants

189 of this model (with and without social preferences; with and without decaying learning rates) to our

190 experimental data for each age cohort and each game, to allow estimating different parameters

191 (learning rates, expectation updating) across cohorts per game (see *Methods*).

192



**Figure 4 | Model of reinforcement learning with social preferences. a**, Individuals acquire monetary payoffs ($) from interactions in the games (*cf*. Figure 1). How they subjectively value each outcome can be influenced by their social preferences (Fehr & Schmidt, 1999), whose impact is proportional to the differences in payoff between interaction partners (δ). **b**, Over the course of the games, individuals update their expectations (*p*) about the behaviour of the other players. The extent of updating is proportional to the prediction error (i.e., the difference between the expected and actual outcome) and learning rate $\lambda$ [43]. **c**, The probability that an individual chooses A (not B) is an increasing function (*F*) of the difference in weight of the two choice options ($w_A$ and $w_B$; Methods). We use maximum likelihood methods to estimate learning rates $\lambda$ for each age cohort and each game separately. In the baseline model, the weights reflect individuals' monetary payoff from their interactions ($) and $\lambda$ is constant over trials. Extended models also incorporate social preferences and learning rates that decay exponentially over game trials (Methods). **d**, For both games, bars show BIC differences of three model variants with the best model, which includes both social preferences (SP) and decaying learning rates. For each model, BIC values were calculated by summing BIC values of all age cohorts. Solid bars reflect models including social preferences; void and hatched bars respectively show models excluding and including decaying learning rates. **e,** Estimated learning rates from the best models as a function of the trial number, for each of the four age cohorts separately for the Trust Game, and **f**, for the Coordination Game. For the older

cohorts (15-18 and 19-23), the estimated learning parameters were virtually identical, causing the plotted lines to coincide.

193

194      For both the Trust Game and the Coordination Game, a comparison of model fits provided

195 strong support for models extended with social preferences (Figure 4d), confirming the results from

196 our behavioural analyses that social preferences impact decision making. The best models also

197 included decaying learning rates (see Figure 4d and Table S7). For the Trust Game, we observe that

198 for the 8-11 year-olds, estimated learning rates are constant over the course of the game, suggesting

199 that in late phases, individuals in this youngest age cohort still updated their expectations of the

200 behaviour in the different social environments. In the older age cohorts, learning rates start high

201 (around $\lambda=1$; asymptote not shown in Figure 4e) and decay over trials, indicating that expectations

202 take form relatively early in the game, and remain relatively stable later on. For the Coordination

203 Game (Figure 4f), we observe a similar pattern: older participants tended to show the strongest

204 decay in learning rates over trials, whereas participants from the younger cohorts tended to update

205 their expectations more early in the game.

206

## Discussion

208      Here, we examined children's, adolescents' and adults' ability to learn to adjust to social

209 environments that differ in their level of cooperation, and examined the role of social preferences

210 (inequality aversion), prior expectations about others' behaviour, and the updating of expectations

211 as potential mechanisms in this behaviour. To this end, participants played a series of economic

212 games with groups of age-matched unfamiliar others, which captured two important cooperative

213 behaviours: trust and coordination behaviour. Our results show a striking developmental asymmetry

214 in the learning to adjust (un)cooperative behaviour: people adjust well to environments that require

215 uncooperative behaviour (i.e., withholding trust, putting oneself ahead) from a young age, yet only

216 learn to adjust to environments that require cooperative behaviours during adolescence. Thus, the

217 chances that cooperative interactions emerge differ substantially between developmental windows.

218 Our results provide several insights into the mechanisms that explain these age-related differences.

219      First, age-related differences in learning to adjust to cooperative behaviours can be partly

220 explained by differences in social preferences. Specifically, older participants showed lower levels of

221 disadvantageous inequality aversion which explained their higher levels of cooperative behaviours.

222 That is, younger participants are less willing to cooperate given that they are more averse to

223 potential non-cooperation of the other player. Moreover, our computational models confirmed that

224 participants' decisions were best captured by a reinforcement learning model extended with social

225 preferences. Together, these results underline that for understanding age-related changes in social -

226    decision making it is critical to understand the development in social preferences, which differ across

227    developmental windows and largely drive social decision-making.

228

229        A potential mechanism that may relate to the influence of inequality aversion on decision

230    making, is behavioural control [22]. Behavioural control refers to the ability to control thoughts and

231    actions in order to regulate behaviour towards (long-term) goals [44,45]. Developmental studies have

232    shown that behavioural control undergoes protracted development due to a prolonged maturation

233    of underlying neural circuitry in regulatory brain regions including the prefrontal cortex [45–47]. In turn

234    this would result in developmental changes in responses to inequality into childhood and

235    presumably into adolescence [23,48]. An experiment in children also confirmed a direct role of

236    behavioural control in behaviour that benefits others: taxing children with a response inhibition task

237    resulted in less prosocial behaviour and more costly punishment to violations of fairness [49] . An

238    alternative explanation is that inequality may evoke stronger emotional responses, such as increased

239    levels of anger [19,50]. This would yield a different view on social preferences in which responses to

240    inequality can be based on emotion regulation ability. Future studies may further disentangle the

241    role of behavioural control and emotion regulation as self-regulatory processes that may drive the

242    development of social preferences and cooperative behaviours. Our findings are consistent with the

243    idea that self-regulatory processes may be a mechanism that attunes cooperative (coordination with

244    unequal outcomes and trust) behaviours more broadly. Consequently, an interesting field for future

245    studies is whether strengthening self-regulatory processes is a promising pathway for stimulating

246    cooperative behaviour in young people.

247        Besides social preferences, we also examined how people's *prior expectations* of others'

248    trustworthiness and inclination to take more than others influenced learning in different social

249    environments. Our results indicated that reported prior expectations of others' behaviour were

250    stable across age cohorts. This is surprising given the consistently reported increase in

251    cooperativeness across age (e.g., [5,12–14]), which was also observed in the current experiment. This

252    suggests that there is a developmental mismatch between prior expectations and the actual levels of

253    cooperation. Moreover, contrary to our hypotheses, we did not find effects of prior expectations on

254    learning to adjust to different social environments. Perhaps people do not have strong prior

255    expectations about others' behaviour in the anonymous games used in the current study, and any

256    expectations they might have are overridden quickly by outcomes of interactions. Presumably,

257    effects of prior expectations in the current setup would be more prominent in a more

258    heterogeneous sample with greater diversity in - for example - life-history backgrounds. For

259    instance, prior expectations (as well as the updating of these expectations), may be different for

260  people who have grown up in an environment where rewards and punishments are unpredictable,
261  this may be particularly the case for children who have experienced harsh and inconsistent
262  discipline, maltreatment and neglect [51,52]. These expectations of others' behaviour may match their
263  environmental experiences and as such, they may engage in social situations differently. Thus, when
264  assessing the generalizability of our results it would be important to include a more heterogeneous
265  sample with greater diversity in life-history backgrounds. Including different populations could also
266  help answering the question to what extent prior expectations about behaviour in games reflect
267  prior expectations about cooperative behaviour in the real world (e.g., [53]).

268  Here we used computational modelling to quantify how quickly children and adolescents
269  updated their expectations based on choice outcomes in previous interactions. Interestingly, when
270  placed in a new social environment, people were initially highly sensitive to behaviours of other
271  players, and quickly adapted their behaviour to the outcomes they experienced. For older ages,
272  behaviour stabilized after a few interactions as signalled by a decrease in learning rate. Children and
273  young-adolescents, however, continued to react to the choices of others across the games. That is,
274  they often switched strategies after a surprising response from one of the environments. This finding
275  indicates that during adolescence, people more effectively integrate outcomes over time, and
276  consequently form stable expectations of others based on their behaviour, which are not quickly
277  overridden by a single experience. Building lasting relations may crucially depend on this integrated
278  information of others' behaviour. Although the continuous expectation updating of children and
279  adolescents hampers their learning in stable environments, this actually may provide an advantage
280  in fast-changing or unpredictable environments [54]. That is, in such environments, immediately
281  responding to changing feedback is more beneficial than sticking to prior expectations [32]. Whether
282  fast-updating better fits children's and adolescents' experienced social environments is an
283  interesting question for future studies.

284  In the current study, participants were confronted with choices from actual peers and real-
285  life consequences of their actions for all interaction partners. This two-directional approach, rather
286  than often-used one-way decision making, is acknowledged as an important aspect of paradigms in
287  social sciences [55]. However, the controlled social environments in our study are less complex than
288  real-life social interactions, in which factors such as social status, culture, or reputation may
289  complicate social decision making. Future studies, e.g., field studies or studies using virtual reality,
290  could aim to further approach the complexity of real-life social interactions, while retaining
291  experimental control. In addition, we included a specific experimental set-up of social learning in
292  which participants were given prior information on the different social environments. Future studies
293  will need to assess whether our developmental findings hold in settings where participants need to

13

294   figure out base rates of cooperativeness and exploitation on their own. Another limitation of the

295   current study is that whereas social preferences were revealed preferences, prior expectations were

296   stated expectations about others. People find it hard to estimate probabilities, and future studies

297   need to assess the validity of these preferences with individual difference measures. Moreover,

298   although IQ did not differ between groups and did not influence any of our findings, our adult

299   participants were mainly recruited through university advertisements. Future studies should aim for

300   a representative sampling strategy in each age cohort. A final limitation of the current study is its

301   cross-sectional design, as longitudinal studies are necessary to identify developmental patterns.

302   Therefore, developmental interpretations of behavioural results and the underlying mechanisms

303   remain speculative.

304   In sum, we combined computational learning models and experimental social manipulations

305   to demonstrate age-related changes in adjusting cooperative behaviours. Well-developed social

306   skills are essential for succeeding in society and long-term positive outcomes. The ability to adapt to

307   different social environments and discern who we should trust and cooperate with, may benefit

308   short-term outcomes, but may also foster social relationships and restrain behavioural and mental

309   health problems in the long-term [1–4]. Knowledge of how such social skills manifest in different

310   developmental stages inform what ages are the important developmental phase for monitoring

311   social development, and what ages are potentially more receptive to interventions [2,56].

312   Our study has shown that adjusting cooperative behaviours is developing rapidly in early

313   adolescence. Improvements in adjustment to different social environments are driven by developing

314   social preferences (waning aversion to disadvantageous inequality aversion) and increasingly

315   effective updating of own behaviour in response to others' behaviour. Early adolescence would,

316   therefore, be a key target window for interventions targeted at stimulating cooperative and well-

317   adjusted social behaviour. Moreover, these findings provide important starting points for

318   interventions for youth with maladaptive social tendencies, such as youth with conduct disorder

319   problems [57,58].

320

## Methods

**Participants**

323   A total of 269 participants (58.4% female) between ages 8 and 23 years took part in this study.

324   Participants were recruited from a primary school (*n* = 60), two secondary schools (*n* = 128), and

325   through local advertisements at a university campus (*n* = 81) in the western and middle part of The

326   Netherlands. The majority of the participants (92.3%) were born in the Netherlands, and a minority

327   was born elsewhere (Marocco 1.4%; all other countries <1%), or information was missing (1.4%).

14

328     Twenty participants from secondary schools (ages 14-16) were excluded due to technical problems

329     with saving the learning data. Four participants were excluded because they did not finish the

330     cognitive behavioural measures, and therefore IQ could not be estimated. The final sample consisted

331     of 245 individuals aged between 8 and 23 years.

332     Adult participants provided written informed consent. For minors, written informed consent

333     was obtained from parents. To make the tasks incentive-compatible, participants were informed

334     that with each behavioural task they could win points that represented lottery tickets. In each class,

335     and in a similar-size group of adults, one lottery ticket was randomly drawn and the winner received

336     a digital 10 Euro gift voucher. In addition, all minors received a small gift; adults received 10 Euros

337     flat rate or course credit. All procedures were approved by the Psychology Research Ethics

338     Committee of Leiden University (minors: CEP17-0301/120; young adults: CEP17-1009/334) and

339     performed in accordance with the relevant guidelines and regulations.

340     For analyses using age cohorts (see *Computational modelling* in the section below), we

341     divided the sample into four roughly equally-sized age cohorts: 8-11 year-olds (n=54, 46.3% female,

342     mean age 10.6, SD 0.9), 12-14 year-olds (n=73, 52.1% female, mean age 13.4, SD 0.7), 15-18 year-

343     olds (n=57, 59.6% female, mean age 17.0, SD 1.3), and 19-23 year-olds (n=61, 80.3% female, mean

344     age 21.1, SD 1.4). A $\chi^2$-test indicated sex differences between age cohorts ($\chi^2_{(3)}$ = 16.6, *P* = 0.001),

345     with more females in the oldest age cohort. IQ was estimated using a speeded version of the Raven

346     Standard Progressive Matrices[59]. The estimated IQ scores were largely within the normal range

347     varying between 79 and 136 (mean IQ = 106, SD = 10.3), and did not differ significantly between age

348     cohorts (*F*(3,237) = 2.18, *P* = 0.090) and sexes (*F*(1,237) = 0.28, *P* = 0.770). Additional analyses

349     showed that sex differences and IQ did not confound performance on the social games, and did not

350     influence any of our observed age-related changes therein (see Tables S2 and S4).

351

352     **Pre-test**

353     A key component of the economic games used in the current study is that choices have

354     consequences not only for oneself, but also for the other player. To ensure this, we performed a pre-

355     test at a separate high school and a separate adult sample (both in The Netherlands) functioning

356     primarily as a match for determining the participants' outcomes and thereby creating a true social

357     consequence of behaviour.

358     In total, 82 adolescents and 44 adults were asked to make one choice (X or Y) for each social

359     game (Trust Game and Coordination Game). We randomly linked each participant in the full-

360     experiment with one pre-test participant. This match and the combined outcomes of their choices

361     determined the outcome for the participants (number of points), as well as for the pre-test

15

362    participant. The pre-test participants had a similar lottery ticket procedure as the participants from

363    the full experiment, i.e., points were lottery tickets with which they had a chance of winning a 10

364    Euro gift voucher. All pre-test participants received a similar instruction as the participants of the

365    main study. That is, it was stressed that their choices would have consequences for themselves and

366    another participant, since their outcomes would result from their combined choices.

367

368    **Economic games: Trust Game and Coordination Game**

369    Participants completed two incentivized economic games: A Trust Game and a Coordination Game

370    (Figure 1). Each game was composed of 30 trials in total: each trial was a one-shot game with a new

371    anonymous player (whose decision had been recorded in the pre-test; see above). Every trial the

372    participants chose between 2 options (A or B) to distribute points between themselves and the

373    other. After their decision they could see the choice of the player (X or Y) and the outcomes for

374    themselves and the player. Outcomes for self and the player resulted from their combined choices,

375    as shown with payoff matrix $\begin{bmatrix} a, a' & b, b' \\ c, c' & d, d' \end{bmatrix}$ where in each of the cells entries with and without

376    apostrophes indicate payoffs for, respectively, the other and self (in bold).

377        In each of the games, the two social environments consisted of 20 players each (but note

378    that participants interacted with only 15 players per environment). Environments are formed based

379    on pre-test responses, which were matched to create a 'cooperative' (73%, i.e., 11 out of 15) and an

380    'uncooperative' social environment (Figure 1). Over the course of the game trials, participants could

381    learn the tendency of choosing X for each environment of other players, and adjust their responses

382    accordingly. Participants were incentivised by associating their performance to the chance of

383    winning a gift voucher (see Supplementary Information for the instruction protocol).

384        The Trust Game (Figure 1b) was characterized by payoff matrix $\begin{bmatrix} 3, 3 & 1, 5 \\ 2, 2 & 2, 2 \end{bmatrix}$. Participants

385    could maximise their earnings by choosing A ('trust'; top row) when matched with a member of the

386    trustworthy environment, and choosing B ('not-trust'; bottom row) when matched with a member

387    of the untrustworthy environment. The Coordination Game (Figure 1d) was characterized by payoff

388    matrix $\begin{bmatrix} 2, 3 & 0, 0 \\ 0, 0 & 3, 2 \end{bmatrix}$. Participants could maximize their earnings by matching their partners' choices,

389    but the one equilibrium (A, X) put the partner ahead, while the other equilibrium put the participant

390    ahead (B, Y).

391        The order of these two games was counterbalanced across participants. Within each game,

392    participants played 30 trials, 15 trials with each environment of players (e.g., trustworthy and

393    untrustworthy environment). The inconsistent choices within an environment (e.g., Y when playing

394    with someone of the environment hat prefers X) were distributed across trials, yet fixed on trials 4,

16

395    8, 12, and 14. Within a game, the order of interactions with the two different environments was

396    presented randomly, yet fixed across participants.

397         Although our main research questions center on the factors specific to learning to adjust

398    behaviour in different social environments (e.g., the role of prior expectations about others, and

399    getting more or less than others), we also included a non-social learning task to examine the level of

400    behavioural adjustment in a simple learning context (Figure S1 and Tables S5-S6). In this non-social

401    learning task, participants played with computers as interaction partners, and only the participant –

402    not the computers – could receive payoffs. A formal comparison between age-related changes in

403    learning to adjust to non-social versus social environments is included in the Supplementary

404    Information. A computational modelling approach on the non-social game is discussed in Figure S4.

405

406    **Social preferences**

407    We measured disadvantageous inequality aversion and advantageous inequality aversion in two

408    separate tasks: respectively, a modified Dictator Game (DG) and Ultimatum Game (UG). These

409    measures were derived from an adapted (i.e., child-friendly and short) version of a DG and UG

410    (based on [60,61]). Participants always performed the DG and UG right before the economic games.

411         In the Dictator Game participants were given six binary choices to divide 10 points between

412    themselves and another anonymous participant in the study; one option was always an unequal

413    distribution (10/0; 10 points for self, 0 points for the recipient) and the other option an equal

414    distribution of points for themselves and the recipient (i.e., starting with (5, 5) and decreasing to (0,

415    0) with each subsequent trial; (4, 4), (3, 3), (2, 2), (1, 1), (0, 0).

416         In the Ultimatum Game, participants responded to six proposals of another anonymous

417    participant in the study on how to divide 10 points. In the case of a rejection both players earn zero,

418    whereas if the participant accepted the offer, the players get the proposed outcome. The first

419    proposal was an equal split but every next proposal was more beneficial for the other than for self

420    (i.e., (5, 5), (4, 6), (3, 7), (2, 8), (1, 9), (0, 10). For both games, we were interested in the point at

421    which a participant switched their preference from an equal to unequal distribution, or vice versa.

422    This allowed us to infer the point at which participants were indifferent between either distribution.

423    This 'indifference point' was used to calculate their inequality aversion ([20]; see Supplemental

424    Information).

425         The values for individuals' disadvantageous inequality aversion varied in discrete logarithmic

426    steps between 0 and 4.5, and values of advantageous inequality aversion varied in linear steps

427    between 0 and 1 (see, e.g. [60]). To ensure that the non-linearity of the UG values did not influence our

428    results, we repeated our GLMMs with participants' calculated indifference points. Note that all of

17

429    our findings remain the same when using indifference points instead of estimated social preferences

430    in analyses.

431        Finally, our estimates of participants' social preferences depend on their level of consistency

432    in choice behaviour in the DG and UG. In total, 54 participants were excluded due to missing values

433    for social preferences (missing disadvantageous inequality aversion, $n = 1$; missing advantageous

434    inequality aversion, $n = 53$). See Supplementary Information, and Figure S2 and S3 for a more

435    detailed description of the Dictator game and Ultimatum Game, and calculation of inequality

436    aversion measures.

437

438    **Prior expectations**

439    Before the start of each of the economic games (Trust Game and Coordination Game), we assessed

440    participants' prior expectations about the behaviour of other people. We asked participants

441    "Suppose that there are 10 other players, how many of these 10 do you think will choose X?" (i.e.,

442    'trustworthy' choice in the Trust Game, or 'other-ahead' choice in the Coordination Game). This

443    resulted in a prior expectation of the trustworthiness of others (Figure 3c) and tendencies to get

444    more than others (Figure 3d), varying from 0 to 10.

445

446    **Procedure**

447    All tests were administered in school settings. In the instruction of each learning task, three control

448    questions were included to ensure understanding of the experimental procedure. Two questions

449    quizzed the participant on their understanding of the point distribution (e.g., type how many points

450    each player was winning in a certain choice combination), and one question referred to the colour

451    denotation of the two environments. If participants failed one of the control questions, the

452    instruction was repeated until participants understood the procedure of the game. For participants

453    younger than 12, instructions were read out load by an experimenter. All participants completed the

454    tasks by themselves on computers in a quiet environment at school or at the university. Background

455    variables such as the Raven SPM (estimated IQ) and several questionnaires (not relevant to the

456    current study) were administered online using Qualtrics (www.qualtrics.com). In a separate session

457    the DG, UG, and learning tasks were completed using the online software LIONESS Lab [62]

458

459    **Statistical analyses of behavioural data**

460    To assess age-related changes in prior expectations and social preferences we ran separate robust

461    linear regression analyses (5000 bootstraps), each with age linear and age quadratic as predictors.

462    Multiple mediation analyses were conducted in SPSS using the computational tool PROCESS version

463   3.3[63]. For indirect effects, 95% (two-tailed) bias-corrected bootstrapped confidence intervals were

464   calculated using 5000 repetitions. An indirect effect is significant if the confidence interval for the

465   indirect effect does not include zero. These analyses were conducted in SPSS 25, and all tests were

466   two-sided.

467

468   **Generalized linear mixed models**

469   To analyse choice behaviour in the Trust Game and Coordination Game, we fitted logistic

470   generalized linear mixed models (GLMMs) to decisions to choose A (coded as 0) or B (coded as 1) to

471   each game separately. Analyses were conducted in R 3.6.1 [64], using the lme4 package [65]). In all

472   models, participant ID entered the regression as a random intercept to handle the repeated nature

473   of the data. Where appropriate, environment was entered as a random slope in our analyses to

474   handle the differences between individuals in their responsiveness to learning to different levels of

475   (non)cooperation. Our GLMMs included a main effect of environment (e.g., trustworthy

476   environment, untrustworthy environment), age in years (linear and quadratic), prior expectations of

477   others' choices and social preferences, and all two-way interactions with environment (see Tables

478   S1-S4 for all GLMM results). Note that for the Trust Game we only added disadvantageous inequality

479   aversion, whereas for the Coordination Game both social preferences were included. That is, in the

480   Coordination Game both types of inequality can occur and drive choice behaviour, in contrast to the

481   Trust Game in which only disadvantageous inequality is present.

482        In all GLMMs, age, prior expectations, disadvantageous and advantageous inequality

483   aversion (mean-centered and scaled) and categorical predictor variables were specified by a sum-to-

484   zero contrast (e.g., sex: -1 = boy, 1 = girl). For the mixed-effects model analyses the optimizer

485   "bobyqa" [67] was used, with a maximum number of $1x10^5$ iterations. P-values for all individual terms

486   were determined by Loglikelihood Ratio Tests as implemented in the mixed function in the afex

487   package[68]. All statistics, including odds ratios and confidence intervals, are reported in Tables S1 –S

488   6.

489

490   **Computational modelling**

491   To gain a mechanistic understanding of participants' learning to adjust in the Trust Game and the

492   Coordination Game, we used a basic reinforcement learning (RL) model[43] and extended it to

493   accommodate social preferences [20] (aversion to unequal outcomes). All our models follow the basic

494   logic of RL, in which agents learn about others behaviour by updating their expectations with

495   experience. In the case of the games, these expectations (denoted $p$) concern the behaviour of their

496   interaction partners (X or Y; cf. Figure 1). In each trial, $p$ is updated with a magnitude proportional to

497   the prediction error (PE; the difference between the actual and expected choice) and the learning

498   rate $\lambda$. Formally, $p_{t+1} = p_t + \lambda \cdot PE$, where $PE = p$ – choice of other (1 if $X$, 0 otherwise). We fit a set of

499   reinforcement learning models to the data to investigate how $\lambda$ changes across age cohorts. This

500   parameter is bounded between 0 (which means no updating of expectations at all) and 1 (which

501   means that expectations match the decision of the most recent player).

502   In our models, the value of $p$ determines the relative weights of $w_A$ and $w_B$ (Figure 4). Each of

503   the games is characterized by a payoff matrix (Figure 1). In each trial $t$, expected monetary payoffs of

504   choosing $A$ or $B$ are respectively given by $w_{A,t}= p_t \cdot a + (1 - p_t) \cdot b$ and $w_{B,t}= p_t \cdot c + (1 - p_t) \cdot d$. We set

505   the initial value of $p_0$ to the cohort mean prior measured in our experiment. The probability that a

506   participant chooses $A$ is determined by a standard softmax function: $\Pr(A) = [1 + e^{-\vartheta \cdot (w_A - w_B)}]^{-1}$. As

507   there are only two options (A and B) to choose from, the probability of choosing $B$ is simply $1 - \Pr(A)$.

508   In the softmax formula, $\vartheta$ reflects 'decision sensitivity' and accounts for stochasticity in participants'

509   choices: low values of $\vartheta$ indicate high levels of stochasticity ($\Pr(A)$ and $\Pr(B)$ tend to be near 0.5), and

510   high values of $\vartheta$ indicate low levels of stochasticity. In our model fits, $\vartheta$ is a free parameter allowed

511   to vary between 0 and 5.

512   We extended this baseline model with two factors. First, we include the cohort mean

513   measures of social preferences; that is, we add the measured cohort averages of *disadvantageous*

514   and *advantageous inequality aversion* to calculate of $w_A$ and $w_B$. In particular, for the Trust Game,

515   the weight of option $A$ was penalized with a value proportional to the disadvantageous inequality

516   aversion (i.e., $\alpha$; note that we drop the subscripts as we assume social preferences to be parameters

517   with a constant value[20] : $w_A= p \cdot a + (1 - p_t) \cdot [ b - \alpha \cdot (b' - b) ]$. As for option $B$ the payoffs for both

518   partners are always equal, $w_B$ is unaffected by social preferences. For the Coordination Game, social

519   preferences can affect the weights of both $A$ and $B$: $w_A= p \cdot \alpha \cdot (a' - a)$, and $w_B= p \cdot \beta \cdot (d - d')$, where

520   $\beta$ denotes advantageous inequality aversion.

521   Second, we allowed the learning rate $\lambda$ to decay over the course of interactions. We

522   implemented this by defining $\lambda_t = \lambda_0 \cdot r^{-\tau}$, where $r$ denotes the trial number, and $\tau$ is a free parameter

523   that reflects the speed of the decay in learning, allowed to vary between 0 and 5. The values of the

524   estimated parameters ($\vartheta, \lambda, \tau$) per age cohort and per game can be found in Table S7. For each of the

525   four age cohorts from Figure 2 separately, we pooled the data and fitted the model with each

526   possible combination of the factors 'social preferences' and 'decay', yielding a total of four models

527   per cohort per game. Note that we also evaluated a potential role for prior expectations by including

528   mean cohort-level prior expectations in the initial valuation of the choice options. However, because

529   prior expectations were relatively close to 5 (range $0 - 10$; Figure 2) this was close to the default

530    expectation *p* of 0.5, marking indifference between the environments at the first choice. Hence, we

531    did not apply formal tests of improved model fit for prior expectations.

532           Figure 4d shows the goodness-of-fit for each model summed across the four age cohorts

533    relative to the best model, which includes both social preferences and decay. We included a

534    simulation study with a parameter recovery component in the Supplementary Information. Our

535    approach of fitting reinforcement learning models to cohort-level data was motivated by the fact

536    that we did have a limited number of observations to accurately fit our model to individual-level

537    choice data. Note that sensitivity analyses with individually-derived parameters indicated this did

538    not influence any of our model-fit conclusions or main findings.

539

540    **Data availability**

541    The data that support the findings of this study will be made available in the Leiden repository:

542    https://openaccess.leidenuniv.nl.

543

544    **Code availability**

545    All relevant R codes will be made available in the Leiden repository:

546    https://openaccess.leidenuniv.nl.

547

## References

1. Crone, E. A. & Dahl, R. E. Understanding adolescence as a period of social–affective engagement and goal flexibility. *Nat. Rev. Neurosci.* **13**, 636–650 (2012).

2. Dahl, R. E., Allen, N. B., Wilbrecht, L. & Suleiman, A. B. Importance of investing in adolescence from a developmental science perspective. *Nature* **554**, 441–450 (2018).

3. Sawyer, S. M., Azzopardi, P. S., Wickremarathne, D. & Patton, G. C. The age of adolescence. *Lancet Child Adolesc. Health* **2**, 223–228 (2018).

4. Paus, T., Keshavan, M. & Giedd, J. N. Why do many psychiatric disorders emerge during adolescence? *Nat. Rev. Neurosci.* **9**, 947–957 (2008).

5. Blakemore, S.-J. & Mills, K. L. Is Adolescence a Sensitive Period for Sociocultural Processing? *Annu. Rev. Psychol.* **65**, 187–207 (2014).

6. Casey, B. J., Jones, R. M. & Hare, T. A. The Adolescent Brain. *Ann. N. Y. Acad. Sci.* **1124**, 111–126 (2008).

7. Chein, J., Albert, D., O'Brien, L., Uckert, K. & Steinberg, L. Peers increase adolescent risk taking by enhancing activity in the brain's reward circuitry: Peer influence on risk taking. *Dev. Sci.* **14**, F1–F10 (2011).

8. van Hoorn, J., van Dijk, E., Meuwese, R., Rieffe, C. & Crone, E. A. Peer Influence on Prosocial Behavior in Adolescence. *J. Res. Adolesc.* **26**, 90–100 (2016).

9. Larson, R. W., Richards, M. H., Moneta, G., Holmbeck, G. & Duckett, E. Changes in adolescents' daily interactions with their families from ages 10 to 18: Disengagement and transformation. *Dev. Psychol.* **32**, 744–754 (1996).

10. Larson, R. & Richards, M. H. Daily Companionship in Late Childhood and Early Adolescence: Changing Developmental Contexts. *Child Dev.* **62**, 284–300 (1991).

11. Rosati, A. G., Benjamin, N., Pieloch, K. & Warneken, F. Economic trust in young children. *Proc. R. Soc. B Biol. Sci.* **286**, 20190822 (2019).

573    12. van den Bos, W., Westenberg, M., van Dijk, E. & Crone, E. A. Development of trust and

574        reciprocity in adolescence. *Cogn. Dev.* **25**, 90–102 (2010).

575    13. Eisenberg, N., Miller, P. A., Shell, R., McNalley, S. & Shea, C. Prosocial development in

576        adolescence: A longitudinal study. *Dev. Psychol.* **27**, 849–857 (1991).

577    14. Eisenberg, N., Carlo, G., Murphy, B. & Van Court, P. Prosocial development in late adolescence: a

578        longitudinal study. *Child Dev.* **66**, 1179–1197 (1995).

579    15. House, B. R. *et al.* Universal norm psychology leads to societal diversity in prosocial behaviour

580        and development. *Nat. Hum. Behav.* **4**, 36–44 (2020).

581    16. Fett, A.-K. J. *et al.* Trust and social reciprocity in adolescence – A matter of perspective-taking. *J.*

582        *Adolesc.* **37**, 175–184 (2014).

583    17. van de Groep, S., Zanolie, K. & Crone, E. A. Giving to Friends, Classmates, and Strangers in

584        Adolescence. *J. Res. Adolesc.* **30**, 290–297 (2020).

585    18. Güroğlu, B., van den Bos, W. & Crone, E. A. Sharing and giving across adolescence: an

586        experimental study examining the development of prosocial behavior. *Front. Psychol.* **5**, (2014).

587    19. van den Bos, W., van Dijk, E. & Crone, E. A. Learning whom to trust in repeated social

588        interactions: A developmental perspective. *Group Process. Intergroup Relat.* **15**, 243–256 (2012).

589    20. Fehr, E. & Schmidt, K. M. A Theory of Fairness, Competition, and Cooperation. *Q. J. Econ.* **114**,

590        817–868 (1999).

591    21. Fehr, E., Bernhard, H. & Rockenbach, B. Egalitarianism in young children. *Nature* **454**, 1079–1083

592        (2008).

593    22. McAuliffe, K., Blake, P. R., Steinbeis, N. & Warneken, F. The developmental foundations of

594        human fairness. *Nat. Hum. Behav.* **1**, 0042 (2017).

595    23. Meuwese, R., Crone, E. A., de Rooij, M. & Güroğlu, B. Development of Equity Preferences in Boys

596        and Girls Across Adolescence. *Child Dev.* **86**, 145–158 (2015).

597    24. Chang, L. J. & Sanfey, A. G. Great expectations: neural computations underlying the use of social

598        norms in decision-making. *Soc. Cogn. Affect. Neurosci.* **8**, 277–284 (2013).

23

599   25. Delgado, M. R., Frank, R. H. & Phelps, E. A. Perceptions of moral character modulate the neural

600        systems of reward during the trust game. *Nat. Neurosci.* **8**, 1611–1618 (2005).

601   26. Ruff, C. C. & Fehr, E. The neurobiology of rewards and values in social decision making. *Nat. Rev.*

602        *Neurosci.* **15**, 549–562 (2014).

603   27. Fareri, D. S., Chang, L. J. & Delgado, M. R. Computational Substrates of Social Value in

604        Interpersonal Collaboration. *J. Neurosci.* **35**, 8170–8180 (2015).

605   28. van den Bos, W., Talwar, A. & McClure, S. M. Neural Correlates of Reinforcement Learning and

606        Social Preferences in Competitive Bidding. *J. Neurosci.* **33**, 2137–2146 (2013).

607   29. Cheong, J. H., Jolly, E., Sul, S. & Chang, L. J. Computational Models in Social Neuroscience. in

608        *Computational Models of Brain and Behavior* (ed. Moustafa, A. A.) 229–244 (John Wiley & Sons,

609        Ltd, 2017). doi:10.1002/9781119159193.ch17.

610   30. Hackel, L. M., Berg, J. J., Lindström, B. R. & Amodio, D. M. Model-Based and Model-Free Social

611        Cognition: Investigating the Role of Habit in Social Attitude Formation and Choice. *Front.*

612        *Psychol.* **10**, 2592 (2019).

613   31. van den Bos, W., Cohen, M. X., Kahnt, T. & Crone, E. A. Striatum–Medial Prefrontal Cortex

614        Connectivity Predicts Developmental Changes in Reinforcement Learning. *Cereb. Cortex* **22**,

615        1247–1255 (2012).

616   32. Decker, J. H., Lourenco, F. S., Doll, B. B. & Hartley, C. A. Experiential reward learning outweighs

617        instruction prior to adulthood. *Cogn. Affect. Behav. Neurosci.* **15**, 310–320 (2015).

618   33. Hauser, T. U., Iannaccone, R., Walitza, S., Brandeis, D. & Brem, S. Cognitive flexibility in

619        adolescence: Neural and behavioral mechanisms of reward prediction error processing in

620        adaptive decision making during development. *NeuroImage* **104**, 347–354 (2015).

621   34. Rosenblau, G., Korn, C. W. & Pelphrey, K. A. A Computational Account of Optimizing Social

622        Predictions Reveals That Adolescents Are Conservative Learners in Social Contexts. *J. Neurosci.*

623        **38**, 974–988 (2018).

624    35. Berg, J., Dickhaut, J. & McCabe, K. Trust, Reciprocity, and Social History. *Games Econ. Behav.* **10**,

625         122–142 (1995).

626    36. Luce, R. D. & Raiffa, H. *Games and Decisions: Introduction and Critical Survey*. (Courier

627         Corporation, 1989).

628    37. Osborne, M. J. & Rubinstein, A. *A course in game theory*. (MIT Press, 1994).

629    38. Daw, N. D., Gershman, S. J., Seymour, B., Dayan, P. & Dolan, R. J. Model-Based Influences on

630         Humans' Choices and Striatal Prediction Errors. *Neuron* **69**, 1204–1215 (2011).

631    39. Behrens, T. E. J., Woolrich, M. W., Walton, M. E. & Rushworth, M. F. S. Learning the value of

632         information in an uncertain world. *Nat. Neurosci.* **10**, 1214–1221 (2007).

633    40. Li, J., Schiller, D., Schoenbaum, G., Phelps, E. A. & Daw, N. D. Differential roles of human striatum

634         and amygdala in associative learning. *Nat. Neurosci.* **14**, 1250–1252 (2011).

635    41. Nassar, M. R. *et al.* Rational regulation of learning dynamics by pupil-linked arousal systems.

636         *Nat. Neurosci.* **15**, 1040–1046 (2012).

637    42. Rescorla, R. A. & Wagner, A. R. A Theory of Pavlovian Conditioning: Variations in the

638         Effectiveness of Reinforcement and Nonreinforcement. 18 (1972).

639    43. Sutton, R. S. & Barto, A. G. *Reinforcement Learning: An Introduction*. vol. 2 (MIT Press, 1998).

640    44. Miller, E. K. & Cohen, J. D. An Integrative Theory of Prefrontal Cortex Function. *Annu. Rev.*

641         *Neurosci.* **24**, 167–202 (2001).

642    45. Steinbeis, N. Neurocognitive mechanisms of prosociality in childhood. *Curr. Opin. Psychol.* **20**,

643         30–34 (2018).

644    46. Achterberg, M., Peper, J. S., van Duijvenvoorde, A. C. K., Mandl, R. C. W. & Crone, E. A.

645         Frontostriatal White Matter Integrity Predicts Development of Delay of Gratification: A

646         Longitudinal Study. *J. Neurosci.* **36**, 1954–1961 (2016).

647    47. van den Bos, W., Rodriguez, C. A., Schweitzer, J. B. & McClure, S. M. Adolescent impatience

648         decreases with increased frontostriatal connectivity. *Proc. Natl. Acad. Sci.* **112**, E3765–E3774

649         (2015).

650    48. Sul, S., Güroğlu, B., Crone, E. A. & Chang, L. J. Medial prefrontal cortical thinning mediates shifts

651         in other-regarding preferences during adolescence. *Sci. Rep.* **7**, 8510 (2017).

652    49. Steinbeis, N. Taxing behavioral control diminishes sharing and costly punishment in childhood.

653         *Dev. Sci.* **21**, e12492 (2018).

654    50. Güroğlu, B., van den Bos, W., van Dijk, E., Rombouts, S. A. R. B. & Crone, E. A. Dissociable brain

655         networks involved in development of fairness considerations: Understanding intentionality

656         behind unfairness. *NeuroImage* **57**, 634–641 (2011).

657    51. Hanson, J. L. *et al.* Early adversity and learning: implications for typical and atypical behavioral

658         development. *J. Child Psychol. Psychiatry* **58**, 770–778 (2017).

659    52. Pitula, C. E., Wenner, J. A., Gunnar, M. R. & Thomas, K. M. To trust or not to trust: social

660         decision-making in post-institutionalized, internationally adopted youth. *Dev. Sci.* **20**, e12375

661         (2017).

662    53. Benz, M. & Meier, S. Do people behave in experiments as in the field?—evidence from

663         donations. *Exp. Econ.* **11**, 268–281 (2008).

664    54. Nussenbaum, K. & Hartley, C. A. Reinforcement learning across development: What insights can

665         we draw from a decade of research? *Dev. Cogn. Neurosci.* **40**, 100733 (2019).

666    55. Camerer, C. & Mobbs, D. Differences in Behavior and Brain Activity during Hypothetical and Real

667         Choices. *Trends Cogn. Sci.* **21**, 46–56 (2017).

668    56. Yeager, D. S., Dahl, R. E. & Dweck, C. S. Why Interventions to Influence Adolescent Behavior

669         Often Fail but Could Succeed. *Perspect. Psychol. Sci.* **13**, 101–122 (2018).

670    57. Frick, P. J. & Viding, E. Antisocial behavior from a developmental psychopathology perspective.

671         *Dev. Psychopathol.* **21**, 1111–1131 (2009).

672    58. Viding, E. & McCrory, E. Towards understanding atypical social affiliation in psychopathy. *Lancet*

673         *Psychiatry* **6**, 437–444 (2019).

674    59. Hamel, R. & Schmittmann, V. D. The 20-Minute Version as a Predictor of the Raven Advanced

675         Progressive Matrices Test. *Educ. Psychol. Meas.* **66**, 1039–1046 (2006).

676  60. Beranek, B., Cubitt, R. & Gächter, S. Stated and revealed inequality aversion in three subject

677      pools. *J. Econ. Sci. Assoc.* **1**, 43–58 (2015).

678  61. Blanco, M., Engelmann, D. & Normann, H. T. A within-subject analysis of other-regarding

679      preferences. *Games Econ. Behav.* **72**, 321–338 (2011).

680  62. Giamattei, M., Yahosseini, K. S., Gächter, S. & Molleman, L. LIONESS Lab: a free web-based

681      platform for conducting interactive experiments online. *J. Econ. Sci. Assoc.* (2020)

682      doi:10.1007/s40881-020-00087-0.

683  63. Hayes, A. F. *Introduction to Mediation, Moderation, and Conditional Process Analysis, Second*

684      *Edition: A Regression-Based Approach*. (The Guilford Press, 2017).

685  64. R Core Team. R: A language and environment for statistical computing. R Foundation for

686      Statistical Computing, Vienna, Austria.URL https://www.R-project.org/ (2020).

687  65. Bates, D., Mächler, M., Bolker, B. & Walker, S. Fitting Linear Mixed-Effects Models using lme4.

688      *ArXiv14065823 Stat* (2014).

689  66. Benjamini, Y. & Hochberg, Y. Controlling the False Discovery Rate: A Practical and Powerful

690      Approach to Multiple Testing. *J. R. Stat. Soc. Ser. B Methodol.* **57**, 289–300 (1995).

691  67. Powell, M. J. D. The BOBYQA algorithm for bound constrained optimization without derivatives.

692      *Tech. Rep. Dep. Appl. Math. Theor. Phys.* 39 (2009).

693  68. Singmann, H., Bolker, B., Westfall, J., Aust, F. & Ben-Sachar, M. S. *afex: Analysis of Factorial*

694      *Experiments*. (2020).

695

696

**Acknowledgements**

We would like to thank all participants and their parents, and the participating schools for their cooperation. We thank Joyce van Amstel, Melanie van Berkel, Annemarijn de Bruin, Yolinda Davidse, Ellina Guijt, Tim Habermehl, Tosca Hunink, Maaike Jacobs, Behazin Khosravi, Sophie van de Leur, Deveney Kok-Sey-Tjong, Liesbeth Roerade, Tess van der Toorn, and Iris Willink for their help with data collection. We thank Jungsun Yoo for help with programming the task, Ruth Roberts for help with formulating the child friendly task instructions, and Eveline Crone for helpful discussions. This work was supported by an Open Research Area (ORA) grant [grant number 464-15-176] financed by the Netherlands Organization for Scientific Research (NWO), the German Research Foundation (DFG) and the Economic and Social Research Council (ESRC). The funder had no role in the conceptualization, design, data collection, analysis, decision to publish, or preparation of the manuscript.

**Author contributions**

B.W., L.M., W.B., E.V., and A.C.K.D. designed the experiment; L.M. programmed the economic games; B.W. collected the data; B.W. and A.C.K.D. performed the behavioural analyses; L.M., W.B., and A.C.K.D. performed the computational modelling; B.W., A.C.K.D, and L.M wrote the main manuscript text; B.W. prepared figures 1-3; L.M. prepared figure 4; all authors interpreted the results and reviewed the manuscript.

**Competing Interests**

The authors declare no competing interests.