Multi-Round Trust Game quantifies inter-individual differences in Social Exchange from Adolescence to Adulthood

Andreas Hula*[1], Michael Moutoussis[2], Geert-Jan Will[3], Danae Kokorikou[4], Andrea Reiter[2], Gabriel Ziegler[5, 14],NSPN Consortium, Ed Bullmore[6,7,8,9], Peter Jones[6,7], Ian Goodyer[6,7], Peter Fonagy[4, 10], P.Read Montague[2,11,12] , Raymond J Dolan[2,9]

1 Austrian Insitute of Technology, Vienna, Austria 2 Wellcome Trust Centre for Neuroimaging, University College London, London, United Kingdom 3 Institute of Psychology, University of Leiden, Leiden, Netherlands 4 Anna Freud Centre, London, United Kingdom 5 Centre for Cognitive Neurology and Dementia Research, Magdeburg, Germany 6 Department of Psychiatry, University of Cambridge, Cambridge, United Kingdom 7 Cambridgeshire and Peterborough National Health Service Foundation Trust, Cambridge, United Kingdom 8 Medical Research Council/Wellcome Trust Behavioural and Clinical Neuroscience Institute, University of Cambridge, Cambridge, United Kingdom 9 Max Planck University College London Centre for Computational Psychiatry, London, United Kingdom 10 Research Department of Clinical, Educational and Health Psychology, University College London, United Kingdom 11 Human Neuroimaging Laboratory, Virginia Tech Carilion Research Institute, Roanoke, Virginia, United States of America 12 Department of Physics, Virginia Polytechnic Institute and State University, Blacksburg, Virginia, United States of America 13 German Center for Neurodegenerative Diseases, Magdeburg, Germany; Please see Appendix for a table of the NSPN consortium.

*Andreas.Hula@ait.ac.at

Abstract:

Investing in strangers in a socio-economic exchange is risky, as we may be uncertain whether they will reciprocate. Nevertheless, the potential rewards for cooperating can be great. Here, we used a cross sectional sample (n = 784) to study how the challenges of cooperation versus defection are negotiated across an important period of the lifespan: through adolescence to young adulthood (ages 14 to 25). We quantified social behaviour using a multi round investor-trustee task, phenotyping individuals using an thoroughly validated model whose parameters characterise patterns of real exchange and constitute latent social characteristics. We found highly significant differences in investment behaviour according to age, sex, socio-economic status and IQ. Consistent with the literature, we showed an overall trend towards higher trust from adolescence to young adulthood but, in a novel finding, we explained this in terms of cognitive mechanisms such as variation in socio-economic risk aversion. We found that lower risk-aversion in males led to greater investments. A number of subtler novel findings included while relative socio-economic deprivation being associated with greater depth of planning but also more defensive play.

Author Summary:

Being able to engage in economically significant exchanges with partners whom we do not know in order to derive mutual benefit is an important social skill in adulthood. We quantified the development of this ability over the period of adolescence to young adulthood using a repeated investment, or ‘trust’ game. We found that the overall willingness to trust an anonymous partner in return for higher potential gains increased with age and IQ, and also varied significantly with socio-economic status and sex.

We previously validated a sophisticated model of the game. This allowed us to characterise participants with respect to important facets of social cognition, including planning, theory of mind, fairness, socio-economic risk aversion, irritability, belief of partner irritability. Our results showed that several of these characteristics varied systematically with age, consistent with a developmental path towards higher social competence from adolescence to young adulthood.

Our findings thus deepen understanding of how the willingness to invest with others develops over this part of the lifespan.

Introduction:

Socio-economic interactions with strangers are inherently risky. However, despite knowing little about potential partners' intentions or probity, we may nevertheless choose to trust them to achieve greater gains for ourselves and to satisfy our own tastes for equity. Learning how much to trust strangers is particularly important during adolescence, as the community of people with whom we interact expands rapidly beyond the bounds of family and local familiarity, and because exploratory collaboration forms a spring-board for longer-term relationships (see Crone & Dahl, 2012, Nelson et al, 2005). Here, we quantify the evolution of the willingness to trust strangers across age 14 to 25.

Economic games offer a rigorous tool for examining the financial, risk-benefit trade-off associated with trusting others. Trust games of various nature have been utilized to study social investment behaviour/trust in diverse samples of adolescents (see van den Bos et al, 2010, van den Bos et al, 2011, van den Bos et al, 2012, Belli et al., 2012, van de Groep 2018) and even young children (see Rosati et al, 2019), with findings varying considerably. Some of these studies have suggested that trust behaviour (investing in an unknown partner with hope of reciprocity) is modulated by the amounts endowed to the investor before reciprocation (which determines 'socio-economic exchange risk') and by sex (female adolescents tending on average to invest less in unknown others), but these effects are not seen in all studies (compare van den Bos et al, 2010). Findings on the development across age of the willingness to invest in anonymous partners during adolescence and young adulthood have yielded conflicting results (for increases see Sutter & Kocher, 2007; van den Bos et al., 2010, for decreases see Derks et al, 2014, with an overview in van de Groep, 2018) and likely depend on the concrete choice of paradigm and age bracket.

A standard work-horse in the study of psychiatric disorders is a multi-round variant of the 'investor-trustee', or multi-round trust task (McCabe et al, 2003, King-Casas et al, 2005) (called the MRT). In the task, one player acts as 'investor', and the other as a 'trustee'. On each of the nine rounds of the game , the investor receives a regular 'wage' from the experimenter and decides on how much of it to invest into the trustee. The experimenter triples the investment, before the trustee chooses the amount of money to return to the investor. Thus, if the investor takes a risk by investing in the trustee, even though the amount of repayment is uncertain, and if the trustee indeed pays back an appropriate amount, both parties benefit from the experimenter's largesse.

The mutual dependency between investor and trustee for maximising their respective outcomes permits a fine-grained study of the ability to establish and maintain cooperation. This task has thus been used to understand the neural underpinnings of personality disorders, the social deficits found in autism, and also aspects of other disorders (see King-Casas,2008, Koshelev et al, 2010, Mellick et al, 2015).

In recent research, detailed computational models of this task (see Ray et al, 2008, Xiang et al, 2012, Hula et al, 2015, Hula et al, 2018) were built. These capture the dynamics of the exchange using a few parameters that quantify key characteristics of each participant. These computational models describe behaviour as arising from an interactive process, wherein participants cannot directly observe the characteristics of others, but can gather information about them from the exchange. At each round, they update beliefs about their partners and act according to their estimates of the long-run worth of their choices. Technically, these features render the task an interactive, partially-observable, Markov decision process (I-POMDP; Gymtrasiewic et al, 2005). Participants are parameterised by their social preference factors (i.e. a socio-economic exchange risk (in the sense of investing in the face of potentially lacking partner reciprocation) and inequity aversion), their capacity to create and avoid ruptures in cooperation, their prior beliefs about these characteristics of their partners, and the sophistication of their theories of other people's minds, all of which we will describe in detail below. In previous work, risk aversion has turned out to be particularly important in describing investors; as this captures a propensity to prefer money that is not put at risk through investing with the trustee over money that is returned through the interaction. . Notably, risk-taking is widely discussed to change markedly from adolescence to adulthood (see Steinberg, 2004, Romer et al, 2017, Defoe et al, 2015), but also to be dependent on other individual factors like sex (see Bach et al, 2020, Reniers et al, 2016, Byrnes et al, 1999, van Duijvenvoorde et al, 2016), socio-economic status and IQ.

Here, we leverage a large (n=784) cross-sectional sample of adolescents and young adults to investigate the relationship of behaviour in the MTG with individual differences regarding age, IQ, sex and socio-economic status. To gain detailed insight into this question, we use our novel computational model to dissociate latent factors contributing to decision-making in this task (namely, theory of mind, planning, social risk aversion, inequality aversion, Irritability, Irritation belief), in order to link them to our inter-individual variables of interest (age, IQ, sex and socio-economic status). Following several examples in the literature, which point towards changes in trust and reciprocity during adolescence (see Fett et al, 2014, Eisenberg et al, 1991, Derks et al, 2014, Belli et al, 2012), we found that differences in risk aversion in the MRT statistically explained a substantial portion of the variability of the investment behaviour observed across participants. Regarding inter-individual differences, we found a marked trend towards higher investments and lower risk aversion with increasing age and IQ (compare Proto et al, 2017). We also found attitudes towards potential partner irritation to change slightly with age, in that subjects seemed less likely to be concerned with irritating their partner in the exchange.

Regarding sex differences, male participants invested significantly more than females. In addition, we found a difference in the attitude towards outcome inequality between male and female subjects, with females being more likely to invest at least a minimum amount in the partner.
Finally, we discovered a previously unreported effect of socio-economic status (SES) on planning in the MRT. There was a significant effect towards longer planning for subjects living in more adverse socio-economic conditions. Together, these effects show various nuances of an increase in social competency with age.

Methods:

Subjects and Data Collection:

We administered the MRT game to a large sample of young people from London or Cambridge who participated in the Neuroscience in Psychiatry Network study (NSPN). We also collected basic demographic variables (age and self-reported sex, referred to as sex), Socio-Economic status (Neighbourhood 'households in poverty index' of the Office of National Statistics 2014) and IQ (Wechsler Abbreviated Scale of Intelligence (WASI) Score, see Weiss et al, 2010). We used raw IQ scores for our analysis. The sample was equally distributed between females and males and between the ages of 14 to 25. Participants were excluded if they currently received help for a psychiatric problem, if they had moderate or severe learning disability or suffered from a serious neurological disorder. For the main analysis, we included only participants for which the above mentioned 4 demographic variables were fully available (n= 784 out of 788 participants who completed the multi round trust game, n=403 female, age range 14-25, mean age 19.05, sd=2.96).

A detailed description of the methodology of the NSPN study can be found in Kiddle et al, 2017.

Ethics Statement:

Participants themselves, and, if they were younger than 16, their legal guardians, provided informed consent. All clinical investigation was conducted according to the principles expressed in the Declaration of Helsinki. The study was approved by the Cambridge Central Research Ethics Committee (12/EE/0250).

The Multiround Investor - Trustee Task

Participants were instructed by trained research assistants about the veridical rules of the game. The task was administered as part of a larger battery of decision-making tasks (see Kiddle et al, 2017).

Participants played the role of the Investor. They were told that they would receive monetary rewards in proportion to their winnings, which was true. As a cover story, they were also led to believe that they were playing with a peer from the same study, playing anonymously from another site, who would also be paid in proportion to their own winnings. Importantly, they did not know the name, sex or any background of their partner. They were asked to play according to their own goals and preferences, rather than optimize an experimenter-specified goal. At the end of the whole study they were debriefed as to the true nature of their ‘partner’, which was a computer algorithm that emulated the behaviour of healthy adult Trustees (see King-Casas et al, 2005).

Participants were encouraged to play as best they could, but were told that the experimenter was interested in how young people made decisions during interactions according to their own preferences and values. Thus, unlike other tasks in the battery, they were not instructed to achieve any particular goal or outcome – this was up to them.

The rules of the game, were as follows (see also Figure 1A). In each of the ten rounds, the investor received an initial endowment of 20 monetary units, or play-coins, and could decide the amount (in whole coins) to transfer to the trustee. The experimenter trebled this quantity and then the trustee (in our case, the computer algorithm mentioned above) decided how many coins to return to the investor: this ranged between 0 coins and the total amount received. The repayment by the trustee was not increased by the experimenter. After the trustee’s action, the investor was informed of the outcome, and the next round started. We thoroughly tested the understanding of participants before the game started, and encouraged them to ask any questions they had. All participants reported here understood the task well, agreed to play it and provided data of adequate quality for analysis.

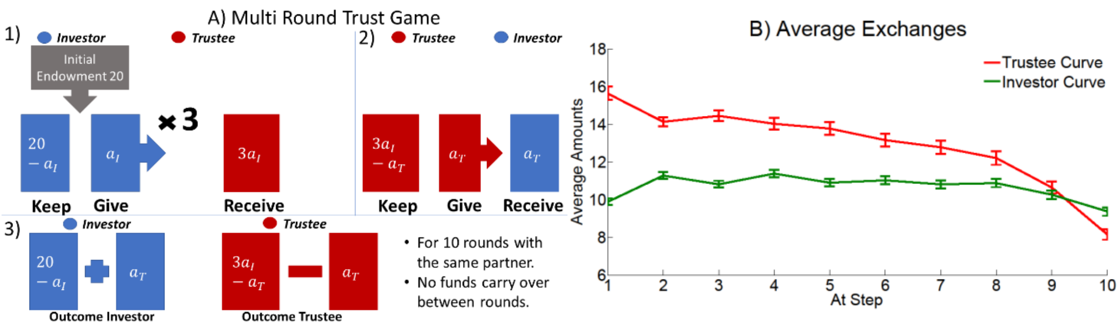

Figure 1: From top left to bottom right: A) Schematic representation of the multi round trust game (MRT). B) Average Investments and Repayments in the MIRT in this study. Errorbars are standard errors of the mean (SEM).

Model:

We modelled behaviour using an interactive, partially observable Markov decision process (I-POMDP) (see Gymtrasiewic et al, 2005). We outline the model here, and describe the seven parameters Θ=($\alpha, \omega, k, P, \zeta, q(\zeta), \ \beta$) that determine the behaviour of our modelled investors, with details on the employed internal state model, inference and statistical properties of the model to be found in Hula et al, 2018 . In short, the I-POMDP is predicated on three structural characteristics: the rules of the task (which define an MDP); the assumed characteristics of the subjects playing the task; and the initial ignorance of the subjects about their partners (leading to partial observability). For computational reasons, we exploited prior studies to restrict the values of the parameters.

According to the I-POMDP characterization, the investor assumes that the trustee processes the information received through the task and makes choices in a structurally similar manner to the investor themselves. In our actual task, this is not formally true, since the trustee is simulated by a computer program that matches the current situation to a database of recorded interactions. Nevertheless, this assumption allows us to build a faithful model of the investors, and thereby interpret their individual characteristics.

We start with positive inequality aversion or guilt, $\alpha \in \{0, 0.4, 1\}$. This quantifies how sensitive a subject is to advantageous unequal outcomes (see Fehr et al, 1999), i.e. how much they prefer an equal outcome. If χ_I denotes the current round outcome of the investor, and χ_T denotes the current round outcome of the trustee, then the subjective utility u_I of the investor with guilt α is

$$u_I = \chi_I - \alpha \max\{\chi_I - \chi_T, 0\}. \qquad (1)$$

where the outcome is

$$\chi_I = (20 - a_I) + a_T. \qquad (2)$$

and

$$\chi_T = 3a_I - a_T. \qquad (3)$$

That is, the utility for an investor with α > 0 is reduced if their associated trustee earns less than themselves. The equivalent is true for the trustee. For the investor, a critical contribution to the trustworthiness of the trustee can be framed as beliefs and learning of the trustee's α.

If the trustee actually has a high value of α, then it is safe for the investor to make a substantial investment. However, in our anonymous setting, the investor does not know the trustee's guilt. Instead, the investor has to learn this from the trustee's behaviour. In principle, the trustee would be in the same position relative to the investor's guilt (although, as noted, in the actual game, the trustee was not actually modelled in this manner). This makes the problem be partially observable – at least some information is not known to the players who therefore are assumed to perform approximate Bayesian inference to accumulate evidence about these unknown factors.

A related parameter ω ∈ $\{0.4, 0.6, 0.8, 1.0, 1.2, 1.4, 1.6, 1.8\}$ quantifies the risk aversion of an investor, i.e. the relative value they accord to the (certain) amount that they keep and do not invest. This is quantified by modifying the notional outcome for the investor, χ_I: If the amount the investor gives is denoted by a_I and the trustee return is denoted by a_T, then

$$\chi_I{}^{true} = \omega(20 - a_I) + a_T. \tag{4}$$

And

$$u_I{}^{true} = \chi_I{}^{true} - \alpha \max\{\chi_I{}^{true} - \chi_T, 0\}. \tag{5}$$

That is, the investor weighs the kept amount $(20 - a_I)$ more $(\omega > 1)$ or less $(\omega < 1)$ than the amount a_T received through the interaction. This automatically weighs the variable (and hence uncertain) repayments differently from the certain amount that is kept. The trustees are subsidiary to the investors in the game, and so are not characterized by this sort of risk aversion. Instead, they would maintain a belief about the investor's risk aversion, denoted as $b^T(\omega) \in \{0.4, 0.6, 0.8, 1.0, 1.2, 1.4, 1.6, 1.8\}$. For simplicity, we assume that the investors think that her partner trustee knows her actual degree of risk aversion.

The most computationally complex parameter is the level of thinking (theory of mind (ToM) level) (see Costa-Gomez et al, 2001, and related Camerer et al, 2004) $k \in \{0,1,2,3,4\}$. Level k-thinking classifies beliefs about the nature of other players by the number of mentalizing steps they employ to model the interaction. Take guilt. A level 0 investor ('she') would build a model of the trustee ('he') based on her beliefs about his degree of "guilt" (see Ray et al, 2008, Xiang et al, 2012, Hula et al, 2015, Hula et al, 2018)]. A level 1 investor would also model the trustee's beliefs about her own degree of guilt. Thus, the investor has to put herself into the trustee's shoes to mentalize what he believes about her. This recurses – thus a level 2 investor would model the trustee's beliefs about her own beliefs about his guilt. The same is true for the trustee modelling the investor. In our models, this potentially unbounded iterative structure of beliefs was limited to four steps, since higher levels do not appear to lead to notably different behaviours (see Hula et al, 2018). We make the further simplifying assumption that a level k investor considers her partner to operate at level $k - 1$.

Next comes parameter $P \in \{1,2,3,4\}$, which quantifies the number of future exchanges to be taken into account in thinking forward. This is called the subject's planning horizon and for the investor it has two main effects (detailed in Hula et al, 2015): longer planning horizons allow for the execution of consistent gameplay strategies and allows to pre-empt exploitation by the partner by realizing initial cooperation might be succeeded by exploitation of the obtained reputation of trust worthiness (in particular taking the form of the trustee no longer repaying fair splits).

Parameter $\zeta \in \{0, 0.25, 0.5, 0.75, 1\}$, called irritability, which provides a model of punishment actions, i.e. sudden investments or repayment close to 0, after an action by the partner that did not satisfy the expectations of an agent. We provide some more detail on this parameter, as it (and the following irritation belief below) might be the most idiosyncratic of the model parameters, since it arose out of the study of BPD data (see also King-Casas et al, 2008). This parameter governs a potential state shift to and from an irritated state, characterised by setting the planning the planning horizon, P, to 0, removing any positive inequality aversion/guilt, α, and failing to model the mental state of the other payer (i.e., when either player is acting irritated, their theory of mind level k is locally set to -1, which implies that they fail to mentalize about the other player at all). The values of all other parameters are kept equal to those in the "nonirritated" state. Irritation can be undone by reciprocating or raising investment despite the irritated partner action. In this case the partner leaves the irritated state again and returns to their 'normal' method for making choices (additional details in Hula et al, 2018).

Additionally, subjects may be able to infer, whether their partner might be irritable. This is realized via approximate Bayesian inference on the partner's irritability parameter based on 5 possible initial belief distributions: Parameter $q(\zeta) \in \{0,1,2,3,4\}$, called "irritation awareness", governs (in a monotonically increasing manner) how sensitive agents are to the possibility of partner irritability (see Hula et al, 2018 for further details), i.e. a subject starts out with different prior weights on the 5 possible values of the partner's ζ, which correspond to "never irritable", "unlikely to be irritable", "possibly irritable", "likely irritable" and "certainly irritable".

Two of the parameters (positive inequality aversion/guilt and irritability) are assumed to be inferred by the agents during the interaction, while the agent assumes all other parameters, (risk aversion, initial irritation belief and planning), to be the same in the partner as in themselves. We followed this strategy because computational constraints and data constraints (i.e., the number of rounds played per subject) limit the number of variables that we can model to be inferred jointly.

The result of all these facets of the problem is that the agent can calculate so-called action values $Q(a|h)$, which quantify the expected value over the future planning horizon of executing action a (an investment or a return) given that the past history of investments and returns is h.

The action values determine action through a logistic softmax function (Eq. 6) with a temperature parameter $\beta \in \left\{\frac{1}{4}, \frac{1}{3}, \frac{1}{2}, \frac{1}{1}\right\}$ to obtain the probability of choosing action a:

$$\mathbb{P}[a|h] = \frac{e^{ßQ(a|h)}}{\sum_c e^{ßQ(c|h)}}. \tag{6}$$

Again for convenience, we constrain a for the investor to take one of five possible values, corresponding to $\{[0,2], [3,7], [8,12], [13,17], [18,20]\}$, being treated as investments of 0, 5, 10, 15 or 20 respectively. Similarly, the trustee returns are discretized to rounded fractions {0, 1/6, 1/3, 1/2 or 2/3) of the tripled investment, i.e., the amount they receive. Returns above 2/3 of the received amount were very rare.

Each subject is classified according to the parameter vector which generated the highest log likelihood for the observed interaction, found by search overall possible parameter values.

A summary of all parameters and their ranges can be found in table 1 below.

PARAMETER SYMBOL	PARAMETER NAME	RANGE	MEANING
$\boldsymbol{\alpha}$	Guilt	$\{0, 0.4, 1\}$	Degree of sensitivity to an unfair outcome against the other player.
$\boldsymbol{\omega}, \boldsymbol{b^T}(\boldsymbol{\omega})$	Risk Aversion	$\left\{\begin{matrix} 0.4, 0.6, 0.8, 1, \\ 1.2, 1.4, 1.6, 1.8 \end{matrix}\right\}$	Multiplier for value of money kept over money returned by the partner.
$\boldsymbol{k}$	ToM Level	$\{0,1,2,3,4\}$	Number of recursive reasoning steps in representing beliefs of the other player.
$\boldsymbol{P}$	Planning	$\{1,2,3,4\}$	Number of steps ahead planned into the interaction.
$\boldsymbol{\zeta}$	Irritability	$\{0, 0.25, 0.5, 0.75, 1\}$	Measure of shift towards punishment behaviour, when experiencing below expectation partner actions.
$\mathbf{q}(\boldsymbol{\zeta})$	Irritation Awareness	$\{0, 1, 2, 3, 4\}$	Awareness of partner irritability. 0 = unaware, 4 = partner for sure irritable.
$\boldsymbol{\beta}$	Inverse Temperature	$\left\{\frac{1}{4}, \frac{1}{3}, \frac{1}{2}, \frac{1}{1}\right\}$	Measure of stochasticity in choices given their expected utilities.

Table 1: Model Parameters, Parameter Ranges and Interpretation of the parameters.

Having inferred values of these parameters from the subjects, we considered whether they were linearly and/or quadratically related to demographic factors.

The average investment and repayment values per round are shown in figure 1B. If the investor gives 10, then any return from the trustee of more than 10 nets the investor with as much as, or more than the trustee, and so represents reliable or over-reciprocating cooperation. Figure 1B shows that the trustee starts out in this manner (automatically reflecting the characteristics of the human participants on which its choices are based); this might coax the investor into investing more. It also reveals that the average investment remained remarkably stable.

To confirm that our generative model pin-pointed key parameters for individual participants, a prerequisite for analysis of individual variation, we used the model to create sample trajectories (1 for each dyad) based on the parameter values that we inferred from the human subjects. Using these generated dyads, we estimated a full set of new parameters. Figure 2A shows the confusion matrix for the parameter that turns out to be most critical: risk aversion. This matrix compares the actual value of the risk aversion on the basis of which a trajectory was created to the value of risk aversion that we inferred from the trajectory. This quantifies the quality of inference about the crucial risk aversion parameter. We found that parameter recovery of risk aversion was very stable and thus inferences based on the risk aversion parameter are justified.

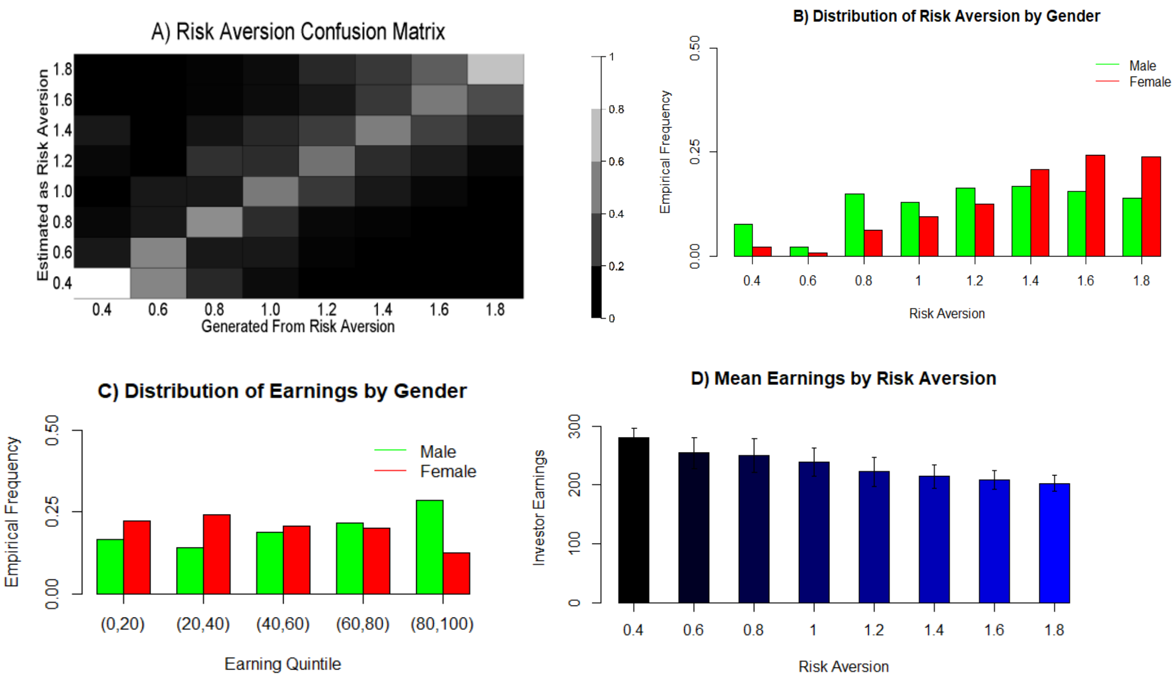

Figure 2: From top left to bottom right. A) Confusion matrix: trajectories were sampled from the generative model using the full collection of parameters inferred from each subject (x-axis); then new parameter values were re-estimated from these trajectories (y-axis). The matrix shows the conditional probability of the re-estimated value of risk aversion as a function of the generating risk aversion. Lighter values indicate higher probabilities. Columns sum to 1. B) Frequency of occurrence of each risk aversion value, separated by sex. C) Average earnings separated by sex and classified according to membership in total earnings quintiles in this study. D) Average investment levels separated by subjects' Risk Aversion parameter. Error bars are standard deviations (SD).

Results:

The model captured behaviour well, the negative loglikelihood (NLL) being 8.09, corresponding to an average 43% of choices being correctly predicted (uniform chance = 20%). We thus proceeded to estimate the proportion of variance in the total investment across all rounds that could be accounted for linearly by the fitted parameters (In Eq. 7 below, ϵ denotes an error term):

$$y = b_0^{\vartheta} + b_k^{\vartheta} k + b_P^{\vartheta} P + b_\alpha^{\vartheta} \alpha + b_\omega^{\vartheta} \omega + b_\beta^{\vartheta} \beta + b_\zeta^{\vartheta} \zeta + b_{q(\zeta)}^{\vartheta} q(\zeta) + \epsilon. \tag{7}$$

This explained a full 69% of the variance (adjusted R^2) of the total investment, while the socio-economic risk aversion parameter ω alone accounted for 44% (adjusted R^2) of the variance.

We then examined how demographic variables may account for social-cognitive characteristics, as captured by model parameters. To assess this, we used linear and quadratic regression for the metric parameters (risk aversion, guilt, temperature, irritability), and ordinal regression for the others (ToM level, Planning and the irritation belief).

Thus, for the metric variables, we considered models of the form

$$\phi = b_0^{\phi} + b_{Age}^{\phi} Age + b_{IQ}^{\phi} IQ + b_{SES}^{\phi} SES + b_{sex}^{\phi} sex + b_{Age^2}^{\phi} Age^2 + b_{IQ^2}^{\phi} IQ^2 + b_{SES^2}^{\phi} SES^2 + \epsilon \tag{8}$$

Here, for sex, we conventionally coded male as 0 and female as 1.

For ordinal regressions (implemented in R (R Core Team, 2017) via the “polr” function), we used

$$l(\mathbb{P}[\phi < i]) = b_{0i}^{\phi} + b_{Age}^{\phi} Age + b_{IQ}^{\phi} IQ + b_{SES}^{\phi} SES + b_{sex}^{\phi} sex + b_{Age^2}^{\phi} Age^2 + b_{IQ^2}^{\phi} IQ^2 + b_{SES^2}^{\phi} SES^2 + \epsilon \tag{9}$$

With a logit link function l and a given level i. We only report significance levels for the variables and not for the intercepts in the ordinal regression.

We started with these full models and employed stepwise model selection, based on the Akaike Information Criterion (AIC), in order to arrive at the most parsimonious model to describe our data. Model selection via the AIC was implemented using via the “stepAIC” function in the statistics language R (see (R Core Team, 2017)). At each step, this considers whether AIC improves upon removing just one term, so tests 7 models in the first step, 6 models in the second, etc., until the AIC can no longer be improved. Below we give the winning model for each parameter and discuss the significant (at p < 0.05) surviving variables in the winning model

For ToM ($\phi = k$), the ultimate model was :

$$l(\mathbb{P}[k < i]) = b_{0i}^{k} + b_{Age}^{k} Age + b_{IQ}^{k} IQ + b_{SES^2}^{k} SES^2 + \epsilon, \tag{10}$$

We found significant negative effects of IQ ($b_{IQ}^{k} = -0.011$, p = 0.003) on the ToM level, which may appear counter-intuitive. We hence investigated, whether there may be empirical correlates with the ToM levels, which might explain this classification. We found that investors classified as level 2 earned an average amount of 228 points (sd of 29.7), while investors classified as level 4 earned an average of 221 points (sd of 28), a difference in the means which was significant in a two-sided t-test at p =0.0027. We then ran a test in the generative model utilizing an α of 0.4 (opportunistic setting), a risk aversion ω of 1.0, a β of 1, no irritability and no assumption of irritability and a planning P of 4, to investigate whether such empirical differences in earnings could be understood in terms of the ToM parameter in the model. The outcomes can be seen in Table 2 below.

MEAN EARNINGS	INVESTOR LEVEL 2	INVESTOR LEVEL 4
TRUSTEE LEVEL 1	220	202
TRUSTEE LEVEL 3	146	187

Table 2: Mean Investor Earnings (kept amount plus trustee repayment) from 120 model generated exchanges as a function of investor and trustee ToM levels for $\alpha = 0.4$, $\beta = 1$, $\omega = 1$, $P = 4$, $q(\zeta) = 0$ and $\zeta = 0$.

This demonstrates that level 4 investors are expected to earn less, due to avoiding potential level 3 trustee exploitation, while still profiting from the exchange with a level 1 trustee, even an opportunistic, exploitative one. The model results are therefore consistent with higher IQ people choosing to play at a lower ToM level than the maximum possible in our model.

For planning ($\phi = P$), the ultimate model was:

$$l(\mathbb{P}[P < i]) = b_{0i}^{P} + b_{SES}^{P} SES + \epsilon, \tag{11}$$

We found a significant ($b_{SES}^{P} = 0.015$, p = 0.017) effect of SES on planning.

For inequality aversion ($\phi = \alpha$), the ultimate model was:

$$\alpha = b_0^{\alpha} + b_{SES}^{\alpha} SES + b_{sex}^{\alpha} sex + \epsilon, \tag{12}$$

We found a significant ($b_{Sex}^{\alpha} = 0.068$, p = 0.005) effect of sex on inequality aversion, females having a higher level of inequality aversion. One empirical correlate of this is the percentage of male or female actors making 0-investments in the data set (total number 247 of 0-investments, 159 by male, 88 by female participants) which is 64.4% of 0-investments for male and 35.6% for female participants. Furthermore, we found a trend effect of SES on inequality aversion ($b_{SES}^{\alpha} = -0.002$, p=0.055). Note that our SES score increases for less well-off conditions i.e. inequality aversion decreased under less advantageous socio-economic conditions, so that this variation in inequality aversion would be consistent with a redistributive pattern in the population.

For risk aversion ($\phi = \omega$) , the ultimate model was:

$$\omega = b_0^{\omega} + b_{Age}^{\omega} Age + b_{IQ}^{\omega} IQ + b_{SES}^{\omega} SES + b_{sex}^{\omega} sex + b_{SES^2}^{\omega} SES^2 + \epsilon, \tag{13}$$

We found highly significant negative relationships between Risk Aversion and Age and IQ, and a significant relationship with sex (respectively: b_{Age}^{ω}= -0.1, $p = 10^{-5}$ for Age, b_{IQ}^{ω}=-0.038, $p = 10^{-10}$ for IQ and b_{sex}^{ω}=0.89, $p = 10^{-11}$ for sex) as well as a positive relation to the SES score ($b_{SES}^{\omega} =$ 0.068,p=0.0075) and a negative relation to the squared SES score ($b_{SES^2}^{\omega} = -0.0011$, p=0.013). For the irritation belief ($\phi = q(\zeta)$), the ultimate model was:

$$l(\mathbb{P}[q(\zeta) < i]) = b_{0i}^{q(\zeta)} + b_{Age}^{q(\zeta)} Age + \epsilon, \tag{14}$$

We found a small, but significant ($b_{Age}^{q(\zeta)} = -0.05$, p = 0.02) effect of Age on the irritation belief.

For the inverse temperature ($\phi = \beta$), the ultimate model was:

$$\beta = b_0^{\beta} + b_{IQ^2}^{\beta} IQ^2 + b_{SES^2}^{\beta} SES^2 + \epsilon, \tag{15}$$

We found no significant effects of IQ squared, and no significant effects of SES^2, despite both factors surviving model selection.

For irritability itself ($\phi = \zeta$) we obtained no noteworthy (i.e. surviving model selection non-constant) relation with the basic demographic variables.

We then investigated the correlations between model parameters in this human data sample. The correlation coefficients and their p-values can be seen in Table 3 below:

	k	P	ω	β	α	ζ	$q(\zeta)$
k	1	0.23 *	-0.02	0.06	0.004	0.05	-0.086 *
P	$8.9\ 10^{-13}$ *	1	0.08 *	-0.12 *	-0.02	-0.02	-0.12 *
ω	0.51	0.004 *	1	-0.06 *	0.32 *	0.08	0.26 *
β	0.07	$5.5\ 10^{-5}$	0.03*	1	-0.05	-0.087 *	-0.35 *
α	0.9	0.5	0	0.1	1	0.025	0.095 *
ζ	0.11	0.45	0.012	0.007	0.45	1	0.03
$q(\zeta)$	0.006	$3.9\ 10^{-5}$	0 *	0	0.002	0.3	1

Table 3: Kendall's tau correlations (diagonal and above) and p-values (below diagonal) of the subject parameters derived from the minimum NLL fit. Asterisk (*) signifies correlations with a p-Value below 0.05. P-values below 10^{-15} denoted as 0.

Parameter correlations reveal that subjects with high theory of mind also tend to have higher planning, both of which are particularly important for precluding trustee exploitation strategies, in an investor. Risk Aversion correlates positively with inequality aversion and irritability belief, that is, subjects with high risk aversion would tend to reliably still give the minimum fair split amount to the partner. The inverse temperature parameter correlates negatively with factors that would make choice preferences more rigid, such as planning and risk aversion. This could result from the need of the model, to still allow sufficient flexibility to fit human data under these circumstances.

We investigated the risk aversion in more depth, as it explained a high proportion of the variance in total investments and was strongly correlated with the socio-demographic variables. We plot the distribution of the risk aversion parameter in figure 2B. Every risk aversion setting occurred in each sex, but in differing proportions. The key difference was an enhanced presence of high risk aversion settings in females compared to males. This influences excess earnings on average of males (significance and 95% confidence interval for the mean difference $\Delta\mu$: $p = 10^{-7}, \Delta\mu \in [8.1, 16.9]$, male mean = 228, sd= 30.4, female mean = 216, sd = 25.25). This represents a small to medium effect size (Cohens d = 0.44). We note that the relevant extremes of the risk aversion distribution are very well reproduced in model-derived simulations, as evidenced by the confusion matrix in figure 2A. Thus, we rule out the possible explanation of this being due to systematic skewing caused through model-fitting. The distribution of membership in one of the 5 earnings quintiles by sex can be seen in figure 2C. This closely matches the respective risk aversion distribution in our generative model. The effects of risk aversion on the obtained earnings of an investor can be seen in figure 2D.

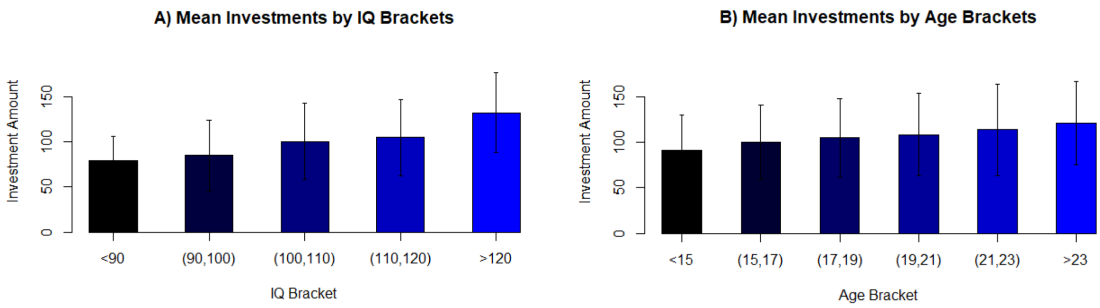

Figure 3. A) Average total Investments ordered by participant age, in 2 year brackets. Error bars are standard deviations (SD). B) Average investments separated by IQ groups (brackets of width 10 IQ points). Error bars are standard deviations (SD).

To illustrate the strongest demographic effects found here, figures 3A and 3B show the relationships between IQ vs. Investment and Age vs. Investment. The monotonic effect of each of these variables on total earnings is readily observed.

Discussion

We analysed the decision-making behaviour of a large cross-sectional sample (n = 784) of 14 to 25 year-olds performing as investors in a social exchange task, in which they chose their preferred level of investment to optimise their own preferences about earnings of themselves and their partners. We employed a well-validated model that quantified investor behaviour according to seven key characteristics, or parameters. In total, these key characteristics explained almost 70% of the variance of the summed investments, hence giving a close account of an important statistic of the success of the social interaction. We found that the novel model-based measure of risk aversion in the MRT (introduced in Hula et al, 2018) alone accounted for 44% of the variance in the total earnings of the subjects. We then considered the relationship between these inferred parameters and various demographic variables.

The socio-economic risk aversion parameter consistently decreased with age, resulting in on average higher investment amounts and earnings in young adults compared to adolescents. This may be an important mechanistic factor in the observed (but not undisputed) relationship in the literature between trust and age during this developmental period (van den Bos et al, 2010). Risk aversion was lower on average in participants with higher IQ and males compared to females, controlling for age and socio-economic status. While this constituted the strongest influence on investment levels, we found a multitude of changes of the seven key characteristics with the four basic demographic variables. Examples include a trend towards inequity averse play to be stronger in females compared to males and a tendency to play with slightly longer planning horizons in subjects living in more adverse socio-economic conditions, as well as a decrease in concern towards possible partner retaliation.

The various dependencies of risk aversion relate in interesting but complex ways to the existing literature. This may partly be because our definition of risk, based on this task is slightly different from that in other framings, for instance including an endowment effect. We observed that socio-economic risk aversion decreased with age between 14 and 25 years of age. Previous findings are that risk aversion outside the context of social exchange increases with age much later in the life span (see Rutledge et al, 2016), or is independent of age (for instance van de Groep et al, 2018). In contrast, and consistent with our findings, trust and reciprocity in trust games has been found to increase over adolescence (in particular van den Bos et al, 2010).

Our finding that risk aversion decreased with IQ is consistent with observations that IQ is correlated with higher investments and earnings, and trust and reciprocity (see Proto et al, 2017). The correlation we found between risk aversion and sex is consistent with others in the literature (see van de Groep et al, 2018, van den Akker et al, 2020, Gneezy et al, 2009, Charness et al, 2012) and in recent work this difference has been the focus of fMRI studies too (see Lemmers-Jansen et al, 2017). However not every study found this effect (see van den Bos et al, 2010). Our findings on the effects of sex on inequality aversion are also consistent with the literature on adults (see for instance Fehr et al, 2006).

Finally, it is notable that in our model we observed a correlation of risk aversion with socioeconomic status. Risk aversion was higher (and thus trust measured as investments lower) in subjects in more adverse socio-economic conditions. This is in line with studies finding positive effects of economic support during adolescence having effects on the behaviour in economic games (see [35]). With our benign trustee, increased risk aversion is unfortunate for this population, implying lower total earnings. ‘

The finding that the planning horizon estimated from the generative model appears to be significantly associated with SES in our sample of adolescents is surprising. Interestingly this effect points to a slight increase of planning with increasing economic disadvantage. Since for the investor planning is essential, in particular for pre-empting exploitation in this game, a possible explanation is that economically disadvantaged subjects were warier of potential defections by the partner.

The fact that theory mind level correlated negatively with IQ and positively with adverse SES bears comment. In particular, the higher level of theory of mind we found (level 4) focuses on preventing exploitation, and was actually associated with lower earnings than the lower level theory of mind (level 2). This reminds us that we are only able to measure expressed theory of mind; if, for instance, a high IQ investor found that a strategy consistent with a lower level theory of mind was effective in a given environment, then they might appropriately stick with it.

The result on decreasing irritation belief with age suggests that irritation-based actions are not the norm among adult partners, and participants learnt this as they aged. This could be related to the development of cognitive control in adolescents (see Zanolie et al, 2018), i.e. subjects might assume that the self-control of others improves with age, just as they may observe their own to do so. This study is subject to limitations that can be addressed in future research. First, the cross-sectional design of our sample limited us to statements about population distributions rather than within-subject, developmental effects. Secondly, the reliability, predictive and construct validity of the MRT remain to be better established, although the present study provides much evidence for its external validity. Related to this, the validity of ‘risk aversion’ in socio-economic exchanges needs to be characterised both in terms of test-retest but also construct validity, including its relation to other measures of risk preference. Fourth, our classification is based on a single instantiation of a social exchange game. Multiple different games and multiple instances of the same game played per subject could potentially yield more robust classifications.

In summary, we have shown effects of age, IQ, SES and sex on the characteristics of social behaviour in the multi-round trust tasks in a large cohort of adolescents. In our task, where participants were free to choose how much to invest in their partner, investment levels rose with increasing age and IQ in a way that was best explained by a decrease in intrinsic risk aversion, rather than other changes in strategy such as changes in theory of mind. Male players across all ages invested significantly more with their partners, which was partially explained by lower risk aversion. We confirmed that our multi parameter generative model could account well for the data, being able reproduce average investment profiles, consistent with previous findings and that our model was able to discover new, more subtle, effects. These included lower socio-economic status being associated with deeper planning in young people, and generally a profile oriented towards avoidance of being exploited. In another subtle effect, expecting irritable behaviour decreased with age (playing in a way that is less concerned about potential partner irritability). Overall, a marked trend towards prosociality and cognitive control can be seen in these findings. Neurobiologically, effects of this kind have been related to neural results on cortical thickness, which can provide a venue for further research using structural MRI and resting state data (see Belluci et al, 2018, Tamnes et al, 2018) in combination with multi round trust game data.

Acknowledgements

RJD is supported by a Wellcome Investigator Award (ref 098362/Z/12/Z). MM and all NSPN consortium authors were supported by Wellcome Strategic Award (ref 095844/7/11/Z); The Max Planck – UCL Centre for Computational Psychiatry and Ageing is a joint initiative of the Max Planck Society and UCL. MM receives support from the UCLH Biomedical Research Centre. PF is n receipt of a National Institute for Health Research (NIHR) Senior Investigator Award (NF-SI-0514-10157). PF was, in part, supported by the NIHR Collaboration for Leadership in Applied Health Research and Care (CLAHRC) North Thames at Barts Health NHS Trust. The views expressed are those of the authors and not necessarily those of the NHS, the NIHR or the Department of Health. The funders had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript. Andrea Reiter acknowledges support by the German Research Foundation (Deutsche Forschungsgesellschaft, DFG RE 4449/1-1).

References:

Bach, D. R., Moutoussis, M., Bowler, A., & Dolan, R. J. (2020). Predictors of risky foraging behaviour in healthy young people. Nature Human Behaviour, 1-12.

Belli, S.R., Rogers, R.D. & Lau, J.Y.F.(2012) Adult and adolescent social reciprocity: Experimental data from the Trust Game, Journal of Adolescence, 35(5), Pages 1341-1349

Bellucci, G., Hahn, T., Deshpande, G. & Krueger, F. (2018) Functional connectivity of specific resting-state networks predicts trust and reciprocity in the trust game, Cognitive, Affective, & Behavioral Neuroscience, https://doi.org/10.3758/s13415-018-00654-3

Byrnes, J. P., Miller, D. C., & Schafer, W. D. (1999). Gender differences in risk taking: A meta-analysis. Washington, DC: American Psychological Association.

Camerer, C.F., Ho, T.H.& Chong, J.S. (2004) A cognitive hierarchy model of games. Quarterly Journal of Economics ; **119**(3): 861-898.

Charness, G. & Gneezy, U. (2012) Strong Evidence for Sex Differences in Risk Taking. Journal of Economic Behavior & Organization; **83**(1): 50-58.

Costa-Gomes, M., Crawford, V.P. & Broseta, B. (2001) Cognition and behavior in normal-form games: An experimental study. Econometrica; **69**(5): 1193-1235.

Crone, E. A., & Dahl, R. E. (2012). Understanding adolescence as a period of social–affective engagement and goal flexibility. Nature Reviews Neuroscience, 13, 636– 650. https://doi.org/10.1038/nrn3313

Defoe, I. N., Dubas, J. S., Figner, B., & van Aken, M. A. (2015). A meta-analysis on age differences in risky decision making: Adolescents versus children, Psychological Bulletin, 141(1), 48–84. https://doi.org/10.1037/a0038088

Derks, J., Lee, N.C. & Krabbendam L. (2014) Adolescent trust and trustworthiness: role of gender and social value orientation. Journal of adolescence , 37(8), 1379-1386.

Eisenberg, N., Miller, P. A., Shell, R., McNalley, S. & Shea, C. (1991) Prosocial development in adolescence: A longitudinal study. Developmental Psychology, 27(5), 849–857.

Fehr, E. & Schmidt, K.M. (1999) A theory of fairness, competition, and cooperation. Quarterly Journal of Economics ; **114**(3): 817-868.

Fehr, E., Naef, M. & Schmidt, K.M. (2006) Inequality Aversion, Efficency and Maximin Preferences in Simple Distribution Experiments: Comment, American Economic Review; 96(5), 1912-1917

Fett, A.K.J., Shergill, S.S., Gromann, P.M., Dumontheil, I., Blakemore, S.J., Yakub, F. & Krabbendam, L. (2014) Trust and social reciprocity in adolescence–a matter of perspective-taking. Journal of adolescence, 37(2), 175-184.

Gmytrasiewicz, P.J.& Doshi, P. (2005) A framework for sequential planning in multi-agent settings. Journal of Artificial Intelligence Research; **24**: 49-79.

Gneezy, U., Leonard, K.L. & List, J.A.(2009) Sex Differences in Competition: Evidence from a Matrilineal and a Patriarchal Society. Econometrica; **77**(5): 1637-1664.

Hula, A., Montague, P.R. & Dayan, P. (2015) Monte Carlo Planning Method Estimates Planning Horizons during Interactive Social Exchange. PLoS Comput Biol ; **11**(6): e1004254.

Hula, A., Vilares, I., Lohrenz, T., Dayan, P. & Montague, P.R. (2018) A Model of Risk and Mental State Shifts during Social Interaction. PLoS Comput Biol ; 14 (2): e1005935

Kiddle, B., Inkster, B., Prabhu, G., Moutoussis, M.& Whitaker, K.(2017) NSPN Consortium N, Jones P. The NSPN 2400 Cohort: a developmental sample supporting the Wellcome Trust Neuroscience in Psychiatry Network.

King-Casas, B., Tomlin, D., Anen, C., Camerer, C.F., Quartz, S.R. & Montague, P.R. (2005) Getting to know you: Reputation and trust in a two-person economic exchange. Science;**308**(5718): 78-83.

King-Casas, B., Sharp, C., Lomax-Bream, L., Lohrenz, T., Fonagy, P. & Montague, P.R. (2008) The rupture and repair of cooperation in borderline personality disorder. Science ; **321**(5890): 806-810.

Koshelev, M., Lohrenz, T., Vannucci, M. & Montague, P.R. (2010) Biosensor Approach to Psychopathology Classification. Plos Computational Biology ; **6**(10).

Lemmers-Jansen, I.L.J., Krabbendam, L., Veltman, D.J. & Fett, A.K.J. (2017) Boys vs. girls: Gender differences in the neural development of trust and reciprocity depend on social context, Developmental Cognitive Neuroscience, Volume 25, Pages 235-245, ISSN 1878-9293, https://doi.org/10.1016/j.dcn.2017.02.001.

Luo, Y., Hétu, S., Lohrenz, T., Hula, A., Dayan, P., Ramey, S.L., Sonnier-Netto, L., Lisinski, J., LaConte, S., Nolte, T., Fonagy, P., Rahmani, E. & Montague, P.R. . (2018) Early childhood investment impacts social decision-making four decades later. Nat Commun 9, 4705. https://doi.org/10.1038/s41467-018-07138-5

McCabe, K., Rigdon, M.L. & Smith, V. (2003) Positive Reciprocity and Intentions in Trust Games. J Econ Behav Organ ; 52(2):267–275.

Mellick, W., Sharp, C. & Ernst, M. (2019) Depressive Adolescent Girls Exhibit Atypical Social Decision-Making In An Iterative Trust Game, Journal of Social and Clinical Psychology, Vol. 38, No. 3, pp. 224-244

Nelson, E. E., Leibenluft, E., McClure, E. B., & Pine, D. S. (2005). The social re-orientation of adolescence: A neuroscience perspective on the process and its relation to psychopathology. Psychological Medicine, 35, 163–174. https://doi.org/10.1017/S0033291704003915

Proto, E., Rustichini, A. & Sofianos, A. (2017) Intelligence, Personality and Gains from Cooperation in Repeated Interactions, CESifo Working Paper Series , 6121

R Core Team. (2017) R: A Language and Evironment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria.

Ray, D., King-Casas, B., Dayan, P. & Montague, P.R. (2008) Bayesian Model of Behaviour in Economic Games. NIPS ; 21:1345–1353.

Reniers, R. L., Murphy, L., Lin, A., Bartolomé, S. P., & Wood, S. J. (2016). Risk perception and risk-taking behaviour during adolescence: the influence of personality and gender. *PloS one*, *11*(4), e0153842.

Romer, D., Reyna, V. F., & Satterthwaite, T. D. (2017). Beyond stereotypes of adolescent risk taking: Placing the adolescent brain in developmental context. Developmental cognitive neuroscience, *27*, 19-34.

Rosati, A.G., Benjamin, N. , Pieloch, K. & Warneken, F. (2019) Economic trust in young children*, Proc. R. Soc. B* 286:. http://dx.doi.org/10.1098/rspb.2019.0822

Rutledge, R.B., Smittenaar, P., Zeidman, P., Brown, H.R., Adams, R.A., Lindenberger, U., Dayan, P.& Dolan, R.J. (2016) Risk Taking for Potential Reward Decreases across the Lifespan. Curr Biol ; **26**(12): 1634-1639.

Steinberg, L. (2004). Risk taking in adolescence: what changes, and why?. In Adolescent Brain Development: Vulnerabilities and Opportunities, Sep, 2003, New York, NY, US.

Sutter, M., & Kocher, M. G. (2007). Trust and trustworthiness across different age groups. Games and Economic Behavior, 59, 364–382. https://doi.org/10.1016/j. geb.2006.07.00

Tamnes, C.K., Overbye, K., Ferschmann, L., Fjell, A.M., Walhovd, K.B., Blakemore, S.J.& Dumontheil, I.(2018) Social Perspective Taking Is Associated With Self-Reported Prosocial Behavior and Regional Cortical Thickness Across Adolescence, Developmental Psychology , Vol. 54, No. 9, 1745–1757 0012-1649/18/$12.00 http://dx.doi.org/10.1037/dev0000541

van den Akker, O.R., van Assen, M.A.L.M., van Vugt, M. & Wicherts, JM. (2020) Sex Differences in Trust and Trustworthiness: A Meta-Analysis of the Trust Game and the Gift-Exchange Game, *psyarxiv*

van den Bos, W., van Dijk, E., & Crone, E. A. (2012) Learning whom to trust in repeated social interactions: A developmental perspective. Group Processes & Intergroup Relations, *15*(2), 243–256

van den Bos, W., van Dijk, E., Westenberg, M., Rombouts S.A & Crone E.A. (2011) Changing brains, changing perspectives: the neurocognitive development of reciprocity. Psychological Science , 22(1), 60-70.

van den Bos, W., Westenberg, M., van Dijk, E. & Crone, E.A. (2010) Development of trust and reciprocity in adolescence. Cognitive Development, 25(1), 90-102.

van Duijvenvoorde, A. C., Peters, S., Braams, B. R., & Crone, E. A. (2016). What motivates adolescents? Neural responses to rewards and their influence on adolescents’ risk taking, learning, and cognitive control. Neuroscience & Biobehavioral Reviews, 70, 135-147.

van de Groep, S., Meuwese, R., Zanolie, K., Güroglu, B., & Crone EA. (2018) Developmental Changes and Individual Differences in Trust and Reciprocity in Adolescence, Journal Of Research On Adolescence, 30(S1), 192–208

Weiss, L.G., Saklofske, D.H., Coalson, D., & Raiford SE. (2010) WASI-IV clinical use and interpretation: Scientist-practitioner perspectives. Academic Press

Xiang, T., Ray, D., Lohrenz, T., Dayan, P., & Montague, P.R. (2012) Computational phenotyping of two-person interactions reveals differential neural response to depth-of-thought. PLoS Comput Biol. 2012;8(12):e1002841. doi:10.1371/journal.pcbi.1002841

Zanolie, K. & Crone, E.A. (2018) Development of Cognitive Control Across Childhood and Adolescence, Stevens' Handbook of Experimental Psychology and Cognitive Neuroscience, Fourth Edition, John Wiley & Sons, Inc. DOI: 10.1002/9781119170174.epcn405

Appendix: The Neuroscience In Psyhiatry Network (NSPN) consortium

Principal investigators:
Edward Bullmore (CI from 01/01/2017)
Raymond Dolan
Ian Goodyer (CI until 01/01/2017)
Peter Fonagy
Peter Jones
NSPN (funded) staff:
Michael Moutoussis
Tobias Hauser
Sharon Neufeld
Rafael Romero-Garcia
Michelle St Clair
Petra Vértes
Kirstie Whitaker
Becky Inkster
Gita Prabhu
Cinly Ooi
Umar Toseeb
Barry Widmer
Junaid Bhatti
Laura Villis
Ayesha Alrumaithi
Sarah Birt
Aislinn Bowler

Kalia Cleridou
Hina Dadabhoy
Emma Davies
Ashlyn Firkins
Sian Granville
Elizabeth Harding
Alexandra Hopkins
Daniel Isaacs
Janchai King
Danae Kokorikou
Christina Maurice
Cleo McIntosh
Jessica Memarzia
Harriet Mills
Ciara O'Donnell
Sara Pantaleone
Jenny Scott
Affiliated scientists:
Pasco Fearon
John Suckling
Anne-Laura van Harmelen
Rogier Kievit