ERC Starting Grant
Research proposal (Part B section 2 (B2))

Section 2: *The Project proposal*: a. State-of-the-art and objectives

From 'Social' to 'Biological' in collective decision making: the challenge of 21st century

I am interested in understanding the neurobiological basis of collective decision making in humans. We continually interact with each other and share information to make decisions together: decisions as friends, families, committees, soldiers, politicians, juries, interest groups and institutions (banks, consumers and citizens in democracies). However, this process is by no means trivial, takes more than simply sharing opinions between people and is far from guaranteed to succeed. Indeed, groups fail to do better than their best individuals alarmingly often and contradictory maxims such as "Two heads are better than one" and "Too many cooks spoil the broth" nicely illustrate the thin line between failure and success in cooperation.

The question how collective decisions are made dates back many centuries [1] and has been vigorously studied in social psychology [2] and many factors have been found to promote or impair joint decisions[3]. However, the biological basis of collective decision making in the human brain is almost entirely unknown. Recent advances in social cognitive neuroscience have now equipped us with conceptual and technological tools that enable us to address this burgeoning question which is arguably at the heart of human society's current and urgent need to communicate effectively and find better ways of arriving at global collective decisions (http://bit.ly/g3nvnx). Grounded in history of social psychology [4,5] and political economics [6,7], my recent research has formalized some of the key psychological components of collective decision making. The stage is now set to address its neurobiological underpinning. To do this, here I propose interdisciplinary research program focusing on 4 main questions:

1) **How do we learn to make better collective decisions?**
2) **What are the functional brain mechanisms underlying the various psychological components of collective decision making?**
3) **What makes some people better and some others worse at collective decision making? Do the brains of prosperous collaborators complement or copy each other?**
4) **What is the role of the "social" neuro-modulatory hormones Oxytocin and Testosterone in collective decision making?**

I will first describe the laboratory model I have been using to study collective decisions. The proposal will then follow in 4 sections. Each section explains a problem and the methodology (including sample size & feasibility considerations) that will be used to address it. The common theme connecting the questions is to use the converging evidence from complementary fields to develop and test a formal theoretical model of collective decision making.

b. Methodology

General. b. Methodology. A model system for Collective Decision Making. I have recently developed a laboratory model for collective decision making [8-10]. In this paradigm (Fig 1), pairs of participants (dyad) together view a brief visual display where a faint target (contrast oddball; Fig1) occurs in either the 1st or 2nd viewing interval. Initially, each participant independently chooses the interval they think contains the oddball, without consulting the other. Individual decisions are then shared, and if disagreeing, participants negotiate until a joint decision is reached. The correct choice is then declared. Individual and dyadic sensitivity and bias as well as the contribution of each person to the collective decision are quantified [9]. The ratio of dyad sensitivity to that of the more sensitive participant quantifies the benefit collective decision making. An ideal computational Bayesian model delineates the upper bound of performance achievable through optimal combination of the individuals' expressed level of confidences in their decisions:

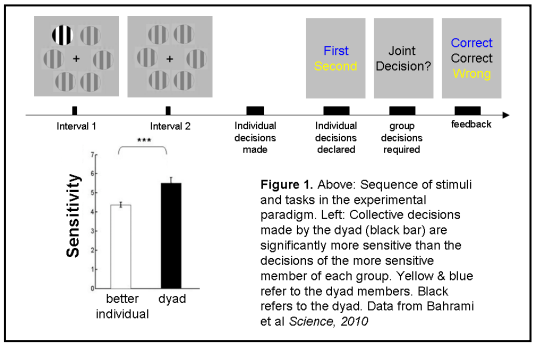

Figure 1. Above: Sequence of stimuli and tasks in the experimental paradigm. Left: Collective decisions made by the dyad (black bar) are significantly more sensitive than the decisions of the more sensitive member of each group. Yellow & blue refer to the dyad members. Black refers to the dyad. Data from Bahrami et al *Science, 2010*

$$s_{group} = \left(s_1 + s_2\right)/\sqrt{2} \qquad \text{(eq. 1)}$$

where S_1 and S_2 are the estimated perceptual sensitivity of the members of the dyad. The ratio of dyad sensitivity to this optimal bound determines how well the dyad has fulfilled its potential. Social interaction significantly improves dyadic perceptual sensitivity (Fig 1) and this benefit is consistently observed across various tasks such as enumeration [11] and joint wagering, with verbal [12] and nonverbal [13] communication modes and even across cultures (tested in UK, Denmark, Iran and China). The results [14] also confirm previous findings on "social facilitation" [15] by showing that engaging in collective decisions

enhances individual's sensitivity in their initial (non-collective decision; Fig 1) Most recently I have compiled a battery of psychological assessment that provides a social personality profile strongly predictive of collective performance. For example, average Empathy Quotient [16]of the dyad members is predictive of the collective benefit. These findings suggest that this model system is not restricted to visual contrast detection but reliably bridges across many previous psychological findings as well as practically relevant forms of joint decision encountered in everyday life. Moreover, the close concordance between the results and the model's predictions suggest that the model captures key features of collective decision making. This paradigm and its numerous results provide the theoretical and psychological foundation for investigating the neurobiological basis of collective decision making..

1) How do we <u>learn</u> to make better collective decisions?

Effective group decision making requires much coordination and practice. However, surprisingly little is known about how people <u>learn</u> to contribute to joint decisions. Moreover, in real life, many joint decisions have to be made without access to immediate outcomes to guide us, sometimes because they are too far in the future e.g. parenting decisions. I recently showed that social interaction enables the build-up of collective benefit even when the decision outcomes are unknown[10]. The paradigm depicted in Fig 1 was used except the dyads never knew who was right or wrong. Dyads did not initially achieve any collective benefit (Fig 2, light grey) but improved over time and by the end equalled the dyads with outcomes (Fig 2, black). This finding is inconsistent with my own previous model [9] which naively made the convenient assumption that collective decision making is a stable process. Current computational models of social learning are based on principles of associative reinforcement learning (RL) [17-19] and invariably depend on outcomes for updating the learning process meaning that they cannot account for no-feedback collective decision making [10] (fig 2) either. Moreover, these models[17-19] are concerned with inferring hidden intentions in the face of conflict of interest whereas, collective decision making is a problem of information integration which persists even without conflict of interest (e.g. what to invest the family savings on). I will therefore develop a new model to account for the build-up of collective decision making by improving information integration across individuals in the absence of conflict of interest and will extend it to situations where outcome is inaccessible.

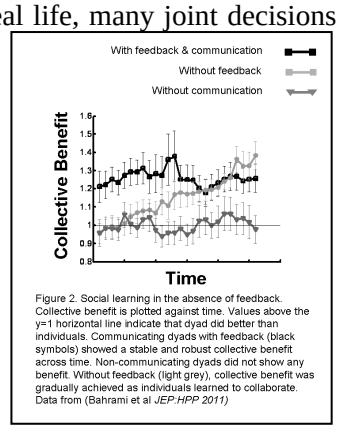

Figure 2. Social learning in the absence of feedback. Collective benefit is plotted against time. Values above the y=1 horizontal line indicate that dyad did better than individuals. Communicating dyads with feedback (black symbols) showed a stable and robust collective benefit across time. Non-communicating dyads did not show any benefit. Without feedback (light grey), collective benefit was gradually achieved as individuals learned to collaborate. Data from (Bahrami et al *JEP:HPP 2011)*

Methods

I propose that learning to make effective collective decisions requires 3 components. Group members should be able to (i) express their own confidence ($\boldsymbol{Z_{self}}$) accurately; (ii) estimate the others' confidence ($\boldsymbol{Z_{other}}$) and (iii) combine the two effectively using the right decision rule. I assume that the absolute values of $\boldsymbol{Z_{self}}$ and $\boldsymbol{Z_{other}}$ are monotonically related to the probability of correct response (1st or 2nd interval) but corrupted by neural and environmental noise. The sign of these values indicate the decisions (-1 = 1st, +1 = 2nd interval). Previously, I have proposed [9] that $Z \propto \Delta C \times S$ where $\Delta\boldsymbol{C}$ is oddball contrast and $\boldsymbol{S}$ is the observer's sensitivity. Consequently, to satisfy components (i) and (ii), members should learn $\boldsymbol{S_{self}}$ and $\boldsymbol{S_{other}}$. Previously, I have proposed [9] that

$$Z_{self} \propto \frac{\Delta C}{\sigma_{self}} \qquad \text{(eq. 2)}$$

$$Z_{other} \propto \frac{\Delta C}{\sigma_{other}} \qquad \text{(eq. 3)}$$

Where $\boldsymbol{\Delta C}$ is the oddball contrast (Fig 1) and $\boldsymbol{\sigma}$ represents noise in the observer's decisions and is inversely related to the observer's contrast sensitivity $\boldsymbol{S}$. As a result, $Z \propto \Delta C \times S$ where $\Delta\boldsymbol{C}$ is oddball contrast and $\boldsymbol{S}$ is the observer's sensitivity. Consequently, to satisfy components (i) and (ii), each person should learn $\boldsymbol{S_{self}}$ and $\boldsymbol{S_{other}}$. Moreover, I define the decision rule by

$$d = f\left(Z_{self} + \beta Z_{other}\right) \qquad \text{(eq. 4)}$$

which gives the probability of confirming the self decision; here $\boldsymbol{\beta}$ is a weighting factor and $f(x) = 1/\left(1 + e^{-\omega x}\right)$ is the logistic sigmoid with $\boldsymbol{\omega}$ reflecting the noise in the dyadic decision. I have previously studied [9] a special case ($\boldsymbol{\beta}=1$) of this formulation under Gaussian assumptions. Component (iii) of social learning seeks to find a value of $\boldsymbol{\beta}$ that maximizes dyad accuracy. Following Hampton and

colleagues [18], I will formulate my model(s) according to the principles of reinforcement learning. The learning model gives a trial-by-trial estimate of S_{self} , S_{other} and β which are updated according to Rescorla-Wagner rule. For example, after trial t, S_{self} is updated by

$$S_{self}^{t+1} = S_{self}^{t} + \eta\delta_{self}^{t} \qquad \text{(eq. 5)}$$

in which δ is the confidence prediction error:

$$\delta_{self}^{t} = R_t - Z_{self}^{t} \qquad \text{(eq. 6)}$$

where Z is the participant's expressed confidence in trial t and R is the correct choice. The model will then be extended to no-feedback cooperation and tested against empirical data (Fig 2, [10]) by replacing R with dyadic decision (i.e. accepting the joint decision as outcome).

Objectives and implications. Once fully developed, I will fit the model to a large database of behavioural experiments I have already conducted using the same paradigm described above to identify the computational strategies employed by interacting humans learning to cooperate effectively. Successful extension of the model to no-feedback condition would suggests that a functional role of shared subjective experience i.e. awareness, may be to replace missing reinforcement when decision outcomes are not available, too complex to estimate or too far in the future to wait for. Given the abundance of situations in everyday life where immediate outcomes are difficult, sometimes even impossible to establish, this idea may offer an ecologically relevant social role for conscious awareness. Moreover, the resulting model will be employed in the analysis of the fMRI data obtained in Experiments 2 & 3 of section 2. The learning parameters (e.g. the employed decision rule, β) will be used in individual difference studies of section 3. The data from the drug study in section 4 will be interrogated by the model to infer the impact of hormonal manipulation on social learning.

Collaborators: One postdoctoral fellow with a PhD in computational neuroscience and decision making will be hired. I will collaborate with Prof. Peter Latham from Gatsby Computational Neuroscience Unit, UCL.

Timetable: This section will take 3 years. In year 1, the main framework of the model will be determined and tested against previously collected empirical data that I have already collected. Year 2 & 3 will be dedicated to developing the model to for analyzing the fMRI experiments (see section 2).

2) What are the functional brain mechanisms underlying the various psychological components of collective decision making?

Recent research in neuroeconomics has identified the mechanisms involved in decision making in isolated individuals that assess and accumulate the evidence favouring each choice option [20], compare the likelihood and magnitude of rewards associated with them [21] and execute the action that implements the decision [22]. In parallel, research in social neuroscience has developed a comprehensive theoretical and empirical picture of the brain mechanisms that contribute to estimating others' intentions and goals [18,19,23]. There is now a growing consensus [17,24] that an urgent next step is to combine these two separate fields to understand the neural basis of human social behaviour. Collective decision making, as the paradigmatic case where social interaction and value-based decision making come together, is the natural setting for these fields to join. Here I propose 3 functional MRI experiments that combine the neuro-economic and socio-cognitive approaches to identify the neuronal substrates of joint decision making.

Experiment 1: I hypothesize that (i) separate neural mechanisms code the self and other's confidence in the human brain; (ii) the weighted combination of self and other's confidence (according to the decision rule defined in question 1) is represented in the human brain. The paradigm will be optimized (Fig 3) for fMRI by a number of key changes following [13,23]. In every session, one recruited participant will be paired with an actor from the lab. The participant performs the task in a MRI scanner and the actor pretends to cooperate by doing the task outside the scanner. The actor's responses will be generated by the computer in a 2x2 factorial design (Fig 3) whereby the participant's (high and low) confidence trials are matched with the actor's high and low confidences. Using an adaptive staircase procedure [25], overall accuracy of participant and actor will be kept equal and stable at 75%. Throughout the experiment, the participant remains oblivious

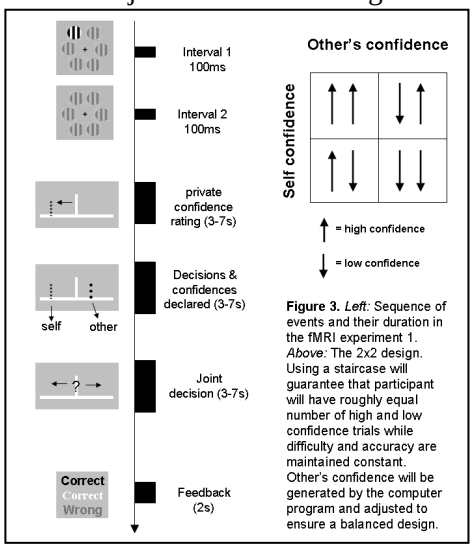

Figure 3. *Left:* Sequence of events and their duration in the fMRI experiment 1. *Above:* The 2x2 design. Using a staircase will guarantee that participant will have roughly equal number of high and low confidence trials while difficulty and accuracy are maintained constant. Other's confidence will be generated by the computer program and adjusted to ensure a balanced design.

to the fact that s/he is collaborating with an actor whose responses are computer generated. In each trial, the participant first makes a private decision about target interval and indicates her/his confidence graphically by how far s/he drags a marker to the left (i.e. 1st interval) or right (2nd interval) of the centre (Fig 3). The actor's decision and confidence will then be declared to participant together with her/his own. She will then make a joint decision for the dyad. Finally feedback will be given. I will use Statistical Parametric Mapping techniques implemented in SPM8 to address my hypotheses. I predict that (i) main effect of Self (see 2x2 design in Fig 3) will identify the right rostral medial [25] and left dorsolateral [26] prefrontal cortex as the regions coding self confidence. (ii) Main effect of Other will identify the anterior [23] and middle [27] cingulate cortex as the regions representing the other's confidence. (iii) A conjunction analysis will be performed to test if the neural representation of self and others are shared. (iv) The neural correlate of the combined confidences (calculated by decision rule in section 1) may be found in the ventromedial prefrontal cortex (VMPFC) [28].

Experiment 2: Using the paradigm of experiment 1 and the social learning model (section 1), I will identify the neuronal correlates of social learning in collective decision making. Critically, here the computer will generate such decisions for the actor that her accuracy will fluctuate in blocks ~20 trials, sometimes more accurate than the participant (who is fixed at ~75%) and sometimes less. Each participant should therefore keep an ongoing track of her partner's accuracy and take her fluctuating reliability into account when making joint decisions. I will then apply the learning model to the behavioural data to infer trial-by-trial estimates of learned self- and other-reliability and the most-likely applied decision rule. I will fit these parameters to the whole-brain fMRI data using model-based fMRI analysis to identify the neuronal correlates of the learning process. I hypothesise that dorsolateral prefrontal cortex [22] is involved in updating the participant's estimate of self reliability and human anterior cingulate cortex tracks the variability in the partner's reliability [23]. Moreover, I also hypothesise that human VMPFC [22] region is involved in updating the decision rule for how to combine self and other's confidence (see section 1). Finally, it is essential to test if any brain areas (identified in experiment 1) contribute to social learning in a manner inconsistent with the predictions of the social collective learning model (section 1)? This latter approach is essential for understanding the model's points of divergence from the biological reality and provides critical information for finding the right direction for advancing the model.

Experiment 3: This experiment complements Experiment 2 towards unravelling the brain mechanisms of social collective learning by examining joint decision making in the absence of feedback. I have recently shown (Fig 2) [10] that feedback has a profound effect on how quickly dyads can achieve benefit from cooperation. The results suggest that, with practice, social interaction can replace the outcome information. Experiment 3 will attempt to find out the neural correlates of this type of social learning. The structure of the experiment will be identical to experiment 1 except that the last stage of each trial (where decision outcomes are declared; Fig 3) will be removed. To analyze the results, I will first re-visit the data from Experiment 1 and 2 to identify the *neural correlates of self-, other- and collective error* separately. I will then examine what happens in the brain in various situations of disagreement in the absence of feedback. For example, I predict that a highly confident disagreeing partner will be interpreted as self- error. Furthermore, model-based approach will be employed to see if the same brain areas that used outcome information in experiment 2 to update belief about reliability of self- and/or other would now employ the joint decision as a *surrogate outcome* to update those beliefs. The results of this experiment will be critical for understanding the mechanisms of joint decision making in numerous everyday life situations when decision outcomes are impossible to establish or too far in the future (e.g. decisions about parenting style).

Sample size: Principled power calculations are known to be difficult in neuroimaging mass-univariate analysis frameworks, so for experiments 1-3, I will adopt the approach now standard in the field of using previous similar studies[23,29] with N=25 subjects that have been able to reject the null hypothesis in one or more voxels.

Time scale: These experiments will be carried out over the period of three years (2013, 14 & 15). Timetable of the experiments is provided in the Table 1.

Collaborators: A postdoctoral research assistant with a PhD in human neuroimaging will be hired in 2013 for carrying out the project. The other RA (hired for section 1) will also contribute to this

	Preparation of Paradigm for fMRI	Data collection	Analysis & write-up	Total
E1	12	10	24	46
E2	14	12	26	52
E3	8	10	20	38

Table 1. Timetable of fMRI experiments
All times are indicated in WEEKS.

project in the model-based fMRI analysis stage.

3) What makes some people better and some others worse at team work? Do the brains of prosperous collaborators COMPLIMENT or COPY each other?

We are not all equally good at joint decisions. What is the biological source of this variability? We have recently shown that individual differences in a range of cognitive faculties spanning sensory perception [30], distractibility in every day life [31], social network size [32] & social influence by others [33] are reflected in the grey matter structure of localized regions in the human brain. I hypothesize that variations in local brain structure are predictive of individuals' ability to contribute to successful collective decisions.

Methods: In a large group of participants, structural MRI and diffusion tensor imaging (DTI) brain scans and social personality profiles will be obtained. The participants will also be paired to undertake the collective decision making paradigm. Using the standard approach of Voxel Based Morphometry and Fractional Anisotropy Analysis in SPM8 (which I have used and taught repeatedly over the past 2 years), I will examine whether local gray matter volume, and white matter connectivity correlate the individuals' contribution to the correct collaborative decisions and social personality profiles. Based on our most recent work on social influence [33], I predict bilateral orbitofrontal cortex (OFC) will show such correlation.

My previous computational work and more recent linguistic analysis of collective decisions suggests that similarity in perceptual sensitivity [9] and convergence to a common, small set of linguistic markers to discuss confidence [12] are crucial predictors of collective success. Is similarity a more general predictor of success in joint decisions? In particular, what are the relational characteristics of successful collaborators' brains? Do the brains of effective collaborators complement or copy each other? To answer these questions, I will take the MRI images of each dyad and for each voxel I will calculate a distance index (DI) (i.e. the difference in grey matter volume between two participants) to construct a dyadic-distance brain (DDB). I will then test whether local variations in DI in the DDB correlate with dyadic collective benefit.

Sample size: Similar to section 2, I will adopt the approach standard in the field of using previous similar studies [30-32] and collect data from N=160.

Timetable: This study will be carried out in 2012-13. Data collection will take ~14 weeks. Analysis & write-ups will take ~14 and ~20 weeks respectively.

Collaborators: Prof. Geraint Rees and Dr. Ryota Kanai at UCL Institute of Cognitive Neuroscience. Two MSc students from 2012 UCL cohort will be recruited to assist with the experiment.

4) What is the role of the *"social" neuro-modulatory hormone* Oxytocin and Testosterone in collective decision making?

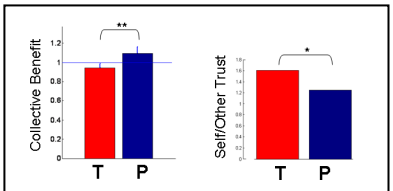

Figure 5. Left : Exogenous testosterone (red) reduced the collective benefit compared to placebo (blue). Right : testosterone also increased the participants' trust in their own decisions (right)

Background: Research over the past decade has shown that understanding the role of neuro-hormonal modulators in interactive contexts is indispensible for social cognitive neuroscience. In the case of collective decision making, striking a balance between self- and other-oriented decisions is essential: for example groups may benefit from a collective intelligence but can become subject to problems such as "group-think"[2]. I have recently discovered [34] (Fig 5) that testosterone causally and selectively disrupts individuals' ability to collaborate fruitfully. Specifically, testosterone impaired collaboration by increasing the individual's self-favouring choices indicating that testosterone reduces interpersonal trust. But effective collaboration requires striking a balance between self- and other-oriented decisions. This suggests that a chemical agent must operate in the opposite direction to testosterone for the brain to maintain balance between self- and other-oriented decisions. I hypothesise that the nanopeptide oxytocin [35] which is involved in social bonding, emotional reaction, birth and lactation – is such a candidate.

Method: A randomised, double-blind, placebo-controlled within-subject design will examine the effect of oxytocin in joint decision making. Normal healthy adult volunteers will self-administer 20-60 IU nasal oxytocin or placebo. Nasal administration of oxytocin affects the processing of social (e.g. emotional faces) and non-social stimuli (e.g. fear conditioning) [35]. After 30-60 minutes, participants will take part in the collective decision task. I hypothesise that exogenous oxytocin will disturb the balance of self versus other

trust in the opposite direction to testosterone and increase pro-social behaviour by promoting other-oriented arbitration in collective decisions. I hypothesise that the impact exogenous oxytocin on collective accuracy, however, will be similar to testosterone (Fig 5, left panel) because any factor that tips the balance of trust (in either direction) will harm joint decisions. The trust hypothesis will be formally investigated by applying the social learning model (section 1) to the data from the testosterone [34] and oxytocin treatments. The prediction is that these two treatments will have opposite effects on learning of self and other sensitivity and lead to biased decision rules that favour self (for testosterone) or the other (for Oxytocin). The model will therefore serve as the link between this experiment and the fMRI data (section 2) to draw new hypotheses for the neural loci of action of testosterone and oxytocin in collective decision making.

Sample size and design: Based on my previous results [34], a sample size of N=40 participants (20 dyads) will provide adequate power for a repeated-measure study. In each session, both participants will receive the same treatment (placebo or drug). Order of treatments will be randomized across dyads. Participants and experimenters will be blind to the treatment in each session.

Timetable: This part of the project will be carried out in 2016-17 (Fig 6). Preparation of the ethics application and approval: ~20 weeks. Data collection: ~10 weeks. Data analysis and write-ups: ~4 and 16 weeks respectively.

Collaborators: Prof. Geraint Rees and Prof. Chris Frith. Two MSc students from the 2016 UCL cohort will be recruited to assist with the experimental procedures.

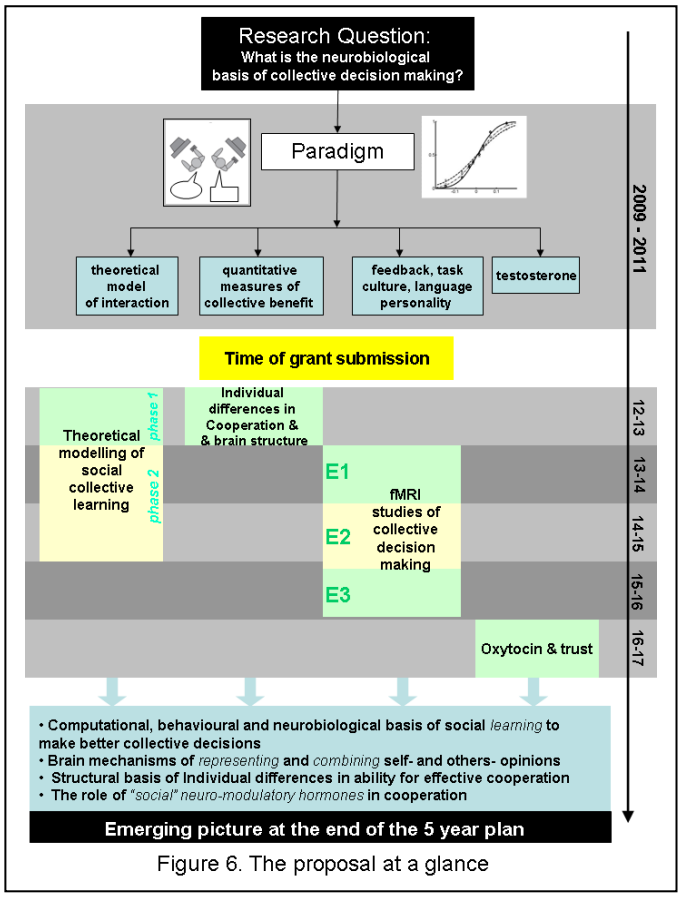

Figure 6. The proposal at a glance

Reference List

1. Condorcet M. (1785). Essai sur l'application de l'analyse á la probabilité des décisions rendues á la pluralité des voix. (Paris: de l'Impr. royale).
2. Kerr N.L. and Tindale R.S. (2004). Group performance and decision making. Annu. Rev. Psychol. 55: 623-655.
3. Hastie R. and Kameda T. (2005). The robust beauty of majority rules in group decisions. Psychol. Rev. 112: 494-508.
4. Galton F. (1907). Vox populi. Nature 75: 450-451.
5. Mackay C. (1841). The extraordinary and popular delusions and madness of crowds, 4 edn. (Ware, UK: Wordsworth Editions Limited).
6. Austen-Smith D. and Banks J. (1996). Information Aggregation, Rationality, and the Condorcet Jury Theorem. The American Political Science Review 90: 34-45.
7. Nitzan S. and Paroush J. (1985). Collective decision making: an economic outlook. (Cambridge: Cambridge University Press).
8. Bahrami B. and Frith C.D. (2011). Interacting minds: a framework for combining process- and accuracy-oriented social cognitive research. Psychological Inquiry 22: 183-186.
9. Bahrami B., Olsen K., Latham P.E., Roepstorff A., Rees G., and Frith C.D. (2010). Optimally interacting minds. Science 329: 1081-1085.
10. Bahrami B., Olsen K., Bang D., Roepstorff A., Rees G., and Frith C. (2011). Together, slowly but surely: The role of social interaction and feedback on the build-up of benefit in collective decision-making. J Exp. Psychol. Hum. Percept. Perform.
11. Bahrami B., Didino D., Frith C.D., Butterowth B., and Rees G (Under review). Collective enumeration.
12. Fusaroli R., Bahrami B., P, Olsen K., Roepstorff A., Frith C., and Tylen K. (Under review). Unfolding cognitive coordination in a state of uncertainty.

13. Bahrami B, Olsen K., Bang D., Roepstorff A, Rees G, and Frith C D (Under review). What failure in collective decision-making tells us about metacognition.
14. Olsen K., Bahrami B., Roepstorff A., and Frith C. (2010). Social interaction enhances the rate of individual visual perceptual learning. In British Association for Cognitive Neuroscience, Annual Scientific Meeting, Bristol UK.
15. ZAJONC R.B. (1965). Social facilitation. Science 149: 269-274.
16. Baron-Cohen S. and Wheelwright S. (2003). The Friendship Questionnaire: an investigation of adults with Asperger syndrome or high-functioning autism, and normal sex differences. J Autism Dev. Disord. 33: 509-517.
17. Behrens T.E., Hunt L.T., and Rushworth M.F. (2009). The computation of social behavior. Science 324: 1160-1164.
18. Hampton A.N., Bossaerts P., and O'Doherty J.P. (2008). Neural correlates of mentalizing-related computations during strategic interactions in humans. Proc. Natl. Acad. Sci. U. S. A 105: 6741-6746.
19. Yoshida W., Dolan R.J., and Friston K.J. (2008). Game theory of mind. PLoS Comput. Biol. 4: e1000254.
20. Gold J.I. and Shadlen M.N. (2007). The neural basis of decision making. Annu. Rev. Neurosci. 30: 535-574.
21. Kable J.W. and Glimcher P.W. (2009). The neurobiology of decision: consensus and controversy. Neuron 63: 733-745.
22. Hare T.A., Schultz W., Camerer C.F., O'Doherty J.P., and Rangel A. (2011). Transformation of stimulus value signals into motor commands during simple choice. Proc. Natl. Acad. Sci. U. S. A.
23. Behrens T.E., Hunt L.T., Woolrich M.W., and Rushworth M.F. (2008). Associative learning of social value. Nature 456: 245-249.
24. Frith C. and Frith U. (2010). Learning from others: introduction to the special review series on social neuroscience. Neuron 65: 739-743.
25. Fleming S.M., Weil R.S., Nagy Z., Dolan R.J., and Rees G. (2010). Relating introspective accuracy to individual differences in brain structure. Science 329: 1541-1543.
26. Heekeren H.R., Marrett S., and Ungerleider L.G. (2008). The neural systems that mediate human perceptual decision making. Nat. Rev. Neurosci. 9: 467-479.
27. Chiu P.H., Kayali M.A., Kishida K.T., Tomlin D., Klinger L.G., Klinger M.R., and Montague P.R. (2008). Self responses along cingulate cortex reveal quantitative neural phenotype for high-functioning autism. Neuron 57: 463-473.
28. Hare T.A., Camerer C.F., and Rangel A. (2009). Self-control in decision-making involves modulation of the vmPFC valuation system. Science 324: 646-648.
29. Behrens T.E., Woolrich M.W., Walton M.E., and Rushworth M.F. (2007). Learning the value of information in an uncertain world. Nat. Neurosci. 10: 1214-1221.
30. Kanai R., Bahrami B., and Rees G. (2010). Human parietal cortex structure predicts individual differences in perceptual rivalry. Curr. Biol. 20: 1626-1630.
31. Kanai R., Dong M.Y., Bahrami B., and Rees G. (2011). Distractibility in daily life is reflected in the structure and function of human parietal cortex. J Neurosci. 31: 6620-6626.
32. Kanai R., Bahrami B., Roylance R., and Rees G. (2011). Online social network size is reflected in human brain structure. Proc. Biol. Sci.
33. Campbell-Meikeljohn D., Kanai R., Bahrami B., Bach D.R., Dolan R.J., Roepstorff A., and Frith C.D. (Under review). Structure of orbitofrontal cortex predicts social influence on value.
34. Wright N., Bahrami B, Johnson E, DiMalta G, Rees G, Frith C.D., and Dolan R. (Under review). Testosterone disrupts human collaboration by increasing egocentric choices.
35. De Dreu C.K., Greer L.L., Handgraaf M.J., Shalvi S., Van Kleef G.A., Baas M., Ten Velden F.S., Van D.E., and Feith S.W. (2010). The neuropeptide oxytocin regulates parochial altruism in intergroup conflict among humans. Science 328: 1408-1411.

c. Resources (incl. project costs)

The PI and each of the RAs will receive 1 desktop and 1 laptop computer. Another desktop computer will be required for data collection, analysis and writing up. An office printer plus toner will be used for letters to the participants plus writing up. Participant expenses (listed under Other Expenses) will be reimbursed at the rate of £10 an hour. MRI scanning (listed under Consumables) is costed at standard rates for hours per annum at the rate of (£548, 575, 604, 634 for successive years) per hour (€ 370,185.0 total) which includes contingency for participant no-show/equipment failure etc. Oxytocin bottles for nasal self-administration are supplied by Pharmaworld (Victoria Apotheke Zurich) at the rate of 40 Swiss Franks per bottle. Each participant will require 2 bottles (i.e. total 80) plus an extra 10 spares. Travel costs consist of two annual trips to UK/Europe for collaboration and one to North America for attendance at the leading conference in the field for the PI and two RA based on round-trip air travel by cheapest route and subsistence at University rates. London allowance is included in the salary.

	Cost Category	**Year 1[1]**	**Year 2[2]**	**Year 3[2]**	**Year 4[2]**	**Year 5[2]**	**Total (Y1-5)[2]**
Direct Costs:	*Personnel:*						
	PI[2]	60461	64646	69122	73912	79044	347,185.00
	Senior Staff						0.00
	Post docs	55659	117,390	125,492	66156	0	364,697.00
	Students						0.00
	Other	3896	4165	4453	4761	5090	22,365.00
	Total Personnel:	**120,016.00**	**186,201.00**	**199,067.00**	**144,829.00**	**84,134.00**	**734,247.00**
	Other Direct Costs:						
	Equipment	10626	4142				14,768.00
	Consumables	77063	123732	90405	84001	7846	383,047.00
	Travel	4809	6413	6658	5384	3988	27,252.00
	Publications, etc	13,649	14,143	14,709	15,298	15,848	73,647.00
	Other						
	Total Other Direct Costs:	106147	148430	111772	104683	27682	**498,714.00**
	Total Direct Costs:	**226,163.00**	**334,631.00**	**310,839.00**	**249,512.00**	**111,816.00**	**1,232,961.00**
Indirect Costs (overheads):	Max 20% of Direct Costs	45,232.60	66,926.20	62,167.80	49,902.40	22,363.20	246,592.20
Subcontracting Costs:	(No overheads)	1,231.00	1,276.00	1,327.00	1,380.00	1,430.00	6,644.00
Total Costs of project:	(by year and total)	272,626.60	402,833.20	374,333.80	300,794.40	135,609.20	1,486,197.20
Requested Grant:	(by year and total)	272,626.60	402,833.20	374,333.80	300,794.40	135,609.20	1,486,197.20

The project cost estimation should be as accurate as possible. The evaluation panels assess the estimated costs carefully; unjustified budgets will be consequently reduced.
There is no minimum contribution per year; the requested contribution should be in proportion to the actual needs to fulfil the objectives of the project.

[1] Adapt to actual project duration.
[2] Please take into account the percentage of your dedicated working time to run the ERC funded activity when calculating the salary. The PI is expected to devote at least 50% of their total working time to the ERC-funded project.

For the above cost table, please indicate the % of working time the PI dedicates to the project over the period of the grant:	**100 %**

Specify briefly your commitment to the project and how much time you are willing to devote to the proposed project in the resources section. Please note that you are expected to devote at least 50% of your total working time to the ERC-funded project and spend at least 50% of your total working time in an EU Member State or Associated Country (see ERC Work Programme 2012).

d. Ethical and Security sensitivity Issues

ETHICS ISSUES TABLE

Areas Excluded From Funding Under FP7 *(Art. 6)*

(i) Research activity aiming at human cloning for reproductive purposes;

(ii) Research activity intended to modify the genetic heritage of human beings which could make such changes heritable (Research relating to cancer treatment of the gonads can be financed);

(iii) Research activities intended to create human embryos solely for the purpose of research or for the purpose of stem cell procurement, including by means of somatic cell nuclear transfer;

All FP7 funded research shall comply with the relevant national, EU and international ethics-related rules and professional codes of conduct. Where necessary, the beneficiary(ies) shall provide the responsible Commission services with a written confirmation that it has received (a) favourable opinion(s) of the relevant ethics committee(s) and, if applicable, the regulatory approval(s) of the competent national or local authority(ies) in the country in which the research is to be carried out, before beginning any Commission approved research requiring such opinions or approvals. The copy of the official approval from the relevant national or local ethics committees must also be provided to the responsible Commission services.

	Research on Human Embryo/ Foetus	YES	Page
	Does the proposed research involve human Embryos?		
	Does the proposed research involve human Foetal Tissues/ Cells?		
	Does the proposed research involve human Embryonic Stem Cells (hESCs)?		
	Does the proposed research on human Embryonic Stem Cells involve cells in culture?		
	Does the proposed research on Human Embryonic Stem Cells involve the derivation of cells from Embryos?		
	I CONFIRM THAT NONE OF THE ABOVE ISSUES APPLY TO MY PROPOSAL	X	

	Research on Humans	YES	Page
	Does the proposed research involve children?		
	Does the proposed research involve patients?		
	Does the proposed research involve persons not able to give consent?		
	Does the proposed research involve adult healthy volunteers?	X	
	Does the proposed research involve Human genetic material?		
	Does the proposed research involve Human biological samples?		
	Does the proposed research involve Human data collection?	X	
	I CONFIRM THAT NONE OF THE ABOVE ISSUES APPLY TO MY PROPOSAL		

	Privacy	YES	Page

	Does the proposed research involve processing of genetic information or personal data (e.g. health, sexual lifestyle, ethnicity, political opinion, religious or philosophical conviction)?		
	Does the proposed research involve tracking the location or observation of people?		
	I CONFIRM THAT NONE OF THE ABOVE ISSUES APPLY TO MY PROPOSAL	X	

	Research on Animals[3]	YES	Page
	Does the proposed research involve research on animals?		
	Are those animals transgenic small laboratory animals?		
	Are those animals transgenic farm animals?		
	Are those animals non-human primates?		
	Are those animals cloned farm animals?		
	I CONFIRM THAT NONE OF THE ABOVE ISSUES APPLY TO MY PROPOSAL	X	

	Research Involving non-EU Countries (ICPC Countries[4]) [5]	YES	Page
	Is the proposed research (or parts of it) going to take place in one or more of the ICPC Countries?		
	Is any material used in the research (e.g. personal data, animal and/or human tissue samples, genetic material, live animals, etc) : a) Collected in any of the ICPC countries?		
	b) Exported to any other country (including ICPC and EU Member States)?		
	I CONFIRM THAT NONE OF THE ABOVE ISSUES APPLY TO MY PROPOSAL	X	

	Dual Use	YES	Page
	Research having direct military use		
	Research having the potential for terrorist abuse		
	I CONFIRM THAT NONE OF THE ABOVE ISSUES APPLY TO MY PROPOSAL	X	

If any of the above issues apply to your proposal, you are required to complete and upload the "B2_Ethical Issues Annex" (template provided).

Without this Annex, your application cannot be properly evaluated and even if successful the granting process will not proceed.

Please see the Guide for Applicants for the Starting Grant 2012 Call for further details and CORDIS http://cordis.europa.eu/fp7/ethics_en.html for further information on how to deal with Ethical Issues in your proposal.

[3] The type of animals involved in the research that fall under the scope of the Commission's Ethical Scrutiny procedures are defined in the Council Directive 86/609/EEC of 24 November 1986 on the approximation of laws, regulations and administrative provisions of the Member States regarding the protection of animals used for experimental and other scientific purposes Official Journal L 358 , 18/12/1986 p. 0001 - 0028

[4] In accordance with Article 12(1) of the Rules for Participation in FP7, 'International Cooperation Partner Country (ICPC) means a third country which the Commission classifies as a low-income (L), lower-middle-income (LM) or upper-middle-income (UM) country. Countries associated to the Seventh EC Framework Programme do not qualify as ICP Countries and therefore do not appear in this list.

[5] A guidance note on how to deal with ethical issues arising out of the involvement of non-EU countries is available at: ftp://ftp.cordis.europa.eu/pub/fp7/docs/developing-countries_en.pdf