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ORIGINAL ARTICLE

Is Kinship a Schema? Moral Decisions and the Function of the Human Kin Naming System

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Abstract The human kinship system, and its associated terminology, bears the hallmarks of an evolutionary adaptation but its evolutionary origins have not been explored. We argue that the human kinship naming system is a schema that evolved to reduce the cognitive load of maintaining kinships, allowing the expansion of the human network and an increase in survival. We report on the results of two response time studies, using moral dilemmas as a proxy for relationship maintenance, which test the hypothesis. We find qualified support for our argument. Within the 50 layer of the social network kinships do impose less cognitive load than friendships allowing a saving in processing power and an increase in social network size beyond that seen in non-human primates. However, the result in the 150 layer is contrary to that posited by our hypothesis: kinships impose a greater load than friendships and this load is highest when refusing help to kin. We explore and discuss the influence on results within this outermost layer of the nature of response, the influence of the wider network and the temporal distance which exists between ego and alter at this level of the network.

Keywords Kinship · Evolution · Social network · Cognitive load

Introduction

Hamilton's theory of kin selection has provided a firm evolutionary basis for our understanding of kinship for more than half a century. However, the rate at which biological relatedness declines with each reproductive event in a pedigree means that kin selection has a relatively narrow biological reach. Beyond cousins, the degree of relatedness is too low to make a great deal of difference. Human kin naming systems, however, invariably extend beyond cousins, and do so using linguistic cues rather than

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conventional biological cues (i.e. proximity during rearing, olfactory cues, etc.) for identifying kin. Although studies of kinship have been common in both traditional anthropology and in human behavioural ecology, the evolutionary reasons why kin naming systems might have evolved have rarely been addressed. While Jones argues that "*…the conceptual structure of kin terms*…[*and*] *kin terms* [*themselves*]*…are built into humans by natural selection*" (Jones 2010:380), he does not proceed to explore why natural selection may have favoured the evolution of this uniquely human system in the first instance. Similarly, the recent two volumes of *Human Nature* (2011) *devoted* to kinship focus almost entirely on the use of evolutionary theory to explain observed behaviour rather than asking any questions about the evolutionary origins of the kin naming system. For the application of evolutionary theory to be comprehensive, we need to ask why this extended kin-identification system evolved in the first instance and what humans gained with its emergence in contrast to the limited rank and kin recognition abilities of non-human primates (Penn et al. 2008; Seyfarth et al. 2005).

There is now extensive, robust, empirical evidence that human social networks are organised as a series of concentric circles which increase in size on a scalar of ~3: the innermost circle contains, on average, 5 individuals, with successively inclusive layers at 15, 50, and 150 (Dunbar et al. 2015; Hamilton et al. 2007; Zhou et al. 2005). Whatever other functions large social networks may have served in the past, there is considerable empirical evidence that the risk of infant and adult mortality, adherence to rehabilitation regimens amongst drug users, survival after a life-threatening illness, adoption of healthy lifestyles and quality of mental, cognitive and physical health are all positively and significantly influenced across age and sex groups by network size and/or involvement in good quality, functional relationships (e.g. Birditt and Antonucci 2008; Chou et al. 2012; Christakis and Fowler 2007; Dominguez and Arford 2010; Fowler and Christakis 2008; Holtzman et al. 2004; Liu and Newschaffer 2011; Min et al. 2007; Pinquart and Duberstein 2010; Rodriguez-Laso et al. 2007; Scelza 2011; Tilvis et al. 2012). A recent meta-analysis of 148 studies found that individuals with adequate social relationships had a 50 % greater chance of survival compared with those with poor or insufficient social relationships. The authors concluded that this put the effect of social relationships on mortality risk on a par with quitting smoking and in excess of that associated with obesity or lack of exercise (Holt-Lunstad et al. 2010). As a consequence, while maintaining ties within a network can be energetically and temporally costly (Roberts and Dunbar 2011a; Roberts et al. 2009), and place a constraint on an individual's freedom to act due to the structural embeddedness of the network, inclusion within a social network can have a significant positive impact on survival.

Our concern, however, is less with the functions of social networks than with the cognitive mechanisms that allow humans to maintain large, coherent networks so as to gain these advantages. Studies of kinship from a cognitive perspective are limited. Read (2008) has argued that the increase in working memory within the *Homo* lineage, evidenced by the increasing complexity in stone tool production, allowed us to extend beyond the simple concepts of kin held by non-human primates (e.g. mother, brother) to complex compound concepts such as mother's brother or aunt's daughter (Read 2008; Read and van der Leeuw 2008). Lieberman et al. (2008) used a memory confusion paradigm to show that kin are implicitly encoded within our psychological architecture to the same extent as sex and age. In one of the very few studies to address the evolutionary origins of kin naming , Brashears (2013) recently suggested that kin labels, in combination with triadic closure (the circumstance where all members of a triad also interact dyadically), act to reduce the cognitive load of maintaining human networks by acting as schema that minimise processing costs when assessing relationships. He showed that participants asked to recall the members and structure of a small social network performed better when the vignettes presented to them contained both kin labels ("cultural schema") and closed triads ("structural schema"). However, while using the terminology of Cognitive Load Theory, Brashears did not explicitly determine whether this improvement in performance resulted from reduced cognitive load as opposed to some alternative cognitive mechanism. Further, Brashears suggests that the ability to employ schema in the recall of kin relationships may explain the increase in group size which occurred with the emergence of *Homo ergaster*. However, aside from the questionable assumption that any species of early *Homo* had language capable of supporting a kin naming system (Dunbar 2008; Read 2008), Brashears does not offer an explanation as to why such an increase in size conferred an advantage at this stage of hominin evolution.

The two studies reported here represent an extension and elaboration of Brashears' study. Using response time as a proxy for cognitive load, we directly test the hypothesis that the kin naming system evolved as a mechanism to reduce the cognitive load of maintaining kin relationships. There is some evidence to suggest that kin relationships require less maintenance, in terms of frequency of contact, than friendships within the same network layer (Roberts and Dunbar 2011a,b). In our experiments, we ask whether kin naming allows individuals to make decisions about future action faster than in the case of friendships. We use moral dilemmas to explore this, since moral dilemmas place an individual in a social bind: faced with a choice between helping or harming an individual who has broken a social taboo, we anticipate that kinship will result in a faster response in favour of the relative. We specifically wished to avoid using a simple recall task, as Brashears did, since we argued that if kinship schemas provide a saving it is because they obviate the need to work through the details of a relationship when deciding how to act towards another individual.

We assume that the kin naming system will be faster because it requires only a single fact (that you are related) to be processed, whereas with friendships we need to backtrack through at least the recent history of the relationship before deciding how to act. We note, as an aside, that while different cultures can classify kin in slightly different ways (Cronk and Gerkey 2010; Keesing 1975), we are here concerned with the psychological mechanisms that underpin linguistic kin classifications, and not with any particular biological basis for kinship. So long as individuals distinguish between kin and nonkin, we are neutral as to how they classify their kin, or even whether there is any biological basis for that classification. Our question is simply whether linguistically classifying some individuals as kin allows us to process decisions about how we should behave towards them faster than if we classify them as nonkin (i.e. as friends in the conventional sense).

Cognitive load (CL) is defined as the total amount of controlled cognitive processing a person engages in to complete a task. Human cognitive architecture consists of Working Memory (WM) and Long Term Memory (LTM). WM is responsible for all conscious tasks and the concurrent processing and storage of information resulting from those tasks (Kirschner 2002). In contrast, LTM is responsible for the storage of information that is required for the individual to understand how to function long-term within their environment: it holds permanent knowledge and skills which provide the context for processing within WM. The individual is not conscious of the knowledge they hold within LTM but it can be moved to WM for conscious processing. LTM is arguably the basis for human intellect as it is capable of storing huge amounts of complex knowledge. Many believe that, in contrast to WM whose capacity and duration is constrained, for practical purposes LTM has a limitless capacity (Paas et al. 2010). Information must pass through WM to be consolidated within LTM and the reverse process occurs when a task requires the individual to access long held knowledge. As a result WM acts as a bottle neck. Only 2 or 3 elements of information can be processed at any one time as WM has to actively organise, compare, contrast and work on the information (Kirschner 2002; Paas et al. 2010). As a result, WM is arguably only capable of completing the simplest of cognitive tasks (Paas et al. 2003a, b).

However, unlike other species, humans appear to have overcome this bottleneck and are capable of complex feats of memory and processing. Cognitive Load Theory (CLT) argues that this has been achieved by the development of schema (Kirschner 2002; Paas et al. 2010). Schema allow related single information elements to be combined into one large element within the LTM and, regardless of the size, richness or complexity of the information, this body of information is read as a single element by WM, allowing the freeing up of processing power within this system. Schema can be added to with new information, several single schemas can be incorporated into a larger schema and ultimately, with practice, the use of schema can become automated, culminating in the removal of any load from the WM as conscious processing is not required (Kirschner 2002; Paas et al. 2003a). As a result of the storage of numerous schema within LTM, humans can handle complex mental tasks which far exceed the capacity of WM.

The load imposed by relationships can be reduced by prior knowledge packaged as schema. Relationships theoretically impose a high load because of the large degree of interaction between their elements, their high emotional content and the fact that, unlike non-social WM tasks, their solution is often open-ended: there is no clear-cut "right" answer (Goddard et al. 1998; Kirschner 2002; Kron et al. 2010; Paas et al. 2003a). Indeed, recent research which focuses exclusively on social WM has found that, in contrast to conventional WM tasks, the processing of social tasks employs two networks—the medial frontoparietal region which is employed in social cognition (including mentalising tasks) and the lateral frontoparietal system which is usually employed in non-social WM tasks—leading to a higher processing cost (Meyer et al. 2012).

We argue here that the emergence of kin naming systems, the characteristics of which are self-evidently analogous to a schema, allowed a significant reduction in processing cost. Further, the establishment of society-wide systems allows the adoption of the system by new members to be akin to the collaborative learning that has been seen to further reduce CL in CLT research (Paas et al. 2010). Kinship terminology encompasses in a single word a range of information about the relationship (e.g. sex, relative age, distance from ego, rank relative to ego, matrikin or patrikin and generation), thereby reducing the cognitive load imposed by the need to orientate oneself within one's network. Further, kin terms not only link ego to another individual but also to a whole set of individuals who are grouped according to their membership of a particular kin group (e.g. mother's relatives) (Jones 2010). This allows an individual to maintain a relationship with a relative without the frequency of contact required by a friendship of similar network position and, arguably, take decisions with regard to reciprocity within that relationship with comparatively reduced levels of load.

Design and Analysis

At the centre of our methodology is the identification of a suitable cognitive task. We required a task which caused the participant to experience a cognitive load, that related in some way to the maintenance of relationships and that was conducive to the measurement of load. In other words, we wanted to avoid the kinds of simple recall task that have been used in previous experiments (e.g. Brashears 2013). For these purposes, we use subjects' responses to moral dilemmas because subjects have to think about how they would deal with a friend or relative who transgresses against the community's social or moral code: would they themselves be willing to break that code in order to protect that friend or relative?

Cognitive load can be measured by a number of methods, the key ones being self-report, response time (primary task), dual task (or interference task) and a range of physiological measures including heart rate variability, brain activity, task-evoked pupillary response and blink rate (Paas et al. 2003b). We selected the second of these methods, response time because it is the simplest to use in an online context.

The combination of a repeated measures task with a dependent variable of time leads to the possibility of a "practice effect", necessitating the use of multilevel modelling (Bryk and Raudenbush 1992). In both studies, a model, with the random variable "SubjectID" at the second level, was built up incorporating, in the first instance, a random intercept and, secondly, random intercept and random slope. The models were tested on the dataset split by Network Layer and then by both Network Layer and Response. This resulted in six models for Study 1 and nine for Study 2. The models investigated the main effect of the Level 1 fixed variables relative-or-friend (RorF), rank, dilemma, sex of subject (SubSex), emotional closeness rating (EC), sex of relative or friend (SexRorF), response (yes vs no), subject age (SubAge) and, in Study 2, the collectivism/individualism scale INDCOL (TotalInd and TotalCol), and the interactions between RorF and SubSex, SexRorF and SubAge on response time. Descriptions of variables are given in Table 1. The move from incorporating a random slope to a random slope and intercept into the models indicated no significant improvement in model fit so only the results pertaining to random slope are given for both studies.

The study is a within-subjects design, so all analyses compare an individual subject's response to a relative with his/her response to a matched friend. Family members and friends are matched for frequency of contact and emotional closeness.

Study 1

This study tested the hypothesis that participants respond quicker to moral dilemmas that involve their kin than to those that involve a friend. Since sex and age of subjects might influence the results, the experimental design included these variables as confounds.

Table 1 Dependent and independent variables

Variable name	Description
SubjectID	Unique subject ID number
Network layer	Layer 1 (15 individuals), 2 (45) or 3 (150) of the Social Network
Time	Response time to question
Response	Yes or No
Rank	Rank number (1–36) assigned to question
SexRorF	Sex of friend or relative
RorF	Whether individual is a relative or friend
Dilemma	Type of dilemma. Dilemmas coded 1–3 in Study 1 and 1–10 in Study 2.
SubSex	Sex of the subject
SubAge	Age of subject
EC	Emotional closeness score (1–10) for relationship

Our hypothesis is that kin naming systems evolved as a mechanism to reduce the cognitive load associated with maintaining extended kin relations. Our main prediction is that:

> H1: Within a given layer of the social network, a cognitive task associated with kinship should impose less of a cognitive load than one associated with friendship, and hence subjects will make faster decisions with respect to kin.

However, we need to control for at least two possible sources of confound, namely a sex difference in response pattern (and especially willingness to act altruistically: e.g. Madsen et al. 2007) and the possible effect of experience (i.e. age). CLT argues that continued use of schema can lead to automation and a reduction in the WM load to zero (Kirschner 2002; Paas et al. 2003a). This appears to be true of facial emotional cue recognition, which initially is assessed consciously in the frontal lobes, but later, from around the mid-20s, becomes automated and is switched to other brain regions (Deeley et al. 2008). Hence, we formulate this as:

> H2: The difference in load between kin- and friendship-related tasks will be greater in those of greater age.

Since women have been found to perform better on social problem tasks involving autobiographical memory, to access autobiographical information and emotions more often in their conversations, to have greater recall of their kin network and to include relatively more kin in their social networks than men, implying that they are better practised at accessing this information (Dunbar and Spoors 1995; Goddard et al. 1998; Roberts et al. 2008, 2009; Salmon and Daly 1996; Sehulster 1995; Stiller and Dunbar 2007). This may suggest that, if the kin naming system is a schema, women should out-perform men because their regular use of the kinship schema will lead to higher levels of automation. Therefore:

> H3: Women will exhibit a greater difference between kin and friends than do men.

Methods

Participants

Participants were recruited from the University of Oxford and via a number of online psychological research sites including Psychological Research on the Net (http://psych.hanover.edu/Research/exponnet.html). Participants were told that the study was intended to explore how they took decisions about their friends and relatives. They were asked to complete the questionnaire in one sitting, avoid distractions and answer the question as soon as they knew the answer. In recalling the names of their relatives and friends they were permitted to use memory prompts such as diaries, Facebook or mobile telephones. Participants were asked to give consent to their inclusion in the study before being allowed to proceed. 149 participants accessed the questionnaire. 28 responses which failed to supply any response time data and 9 responses which had not been completed in one sitting were excluded from analysis. 112 participants (83 female, 19 male and 10 unknown) provided valid responses. The mean age of participants was 32.71 years (range 18–75). 65 % of participants originated from North America, 19 % from the United Kingdom, 6 % from South America, 4 % from Australia and the remaining participants from the European continent and Southern Asia.

Procedure

Participants were asked to recall the first names of one friend and one relative of each sex who were over the age of 18 years from the 15, 50 and 150 layers of their personal social network (12 'alters' in all). To identify the position of the friend or relative within the network, we used questions relating to time of last contact which, along with emotional closeness, has been shown to be the key significant factor placing alters within ego's network (Roberts and Dunbar 2011b; Sutcliffe et al. 2012). A contact in the last month corresponds to the 15 layer (the "sympathy group", Layer 1 in our analysis); one in the last few months but not the last month corresponds to the 50 layer (the "affinity group": Layer 2 in our analysis) and a contact in the last year but not the last few months corresponds to the 150 layer (the "active network", Layer 3 in our analysis) (Sutcliffe et al. 2012). They were also asked to rate the quality of each of these nominated relationships (today, rather than what it had been in the past or how they hoped it might be in the future) in terms of (i) length of the relationship and (ii), on a scale of 1–10, how emotionally close they felt to the person (Emotional Closeness, EC, scale: Marsden and Campbell 1984). Participants also provided brief demographic information relating to their own age, sex and place of birth.

The second section of the questionnaire related to the "Dilemma Task". Here subjects were presented with the three moral dilemma vignettes:

1. A friend/relative confides to you that they have burgled a house and stolen money and jewellery, you promise never to tell. Discovering that an innocent person has been accused of the crime, you plead with your friend/relative to give themself up. They refuse and remind you of your promise. Would you tell the police if the following friend or relative had carried out the crime mentioned above?

2. You are responsible for filling a position at work. Your friend/relative has applied and is qualified, but another candidate is more qualified. Would you give the following friend or relative the job?
3. You and your friend/relative attend the same university. They are taking a course which you completed last year. One day they approach you and tell you that the final essay for the course is due tomorrow but they have been unable to complete it due to personal problems. If they do not hand in an essay they will fail the course and have to retake the year. They ask to borrow your essay from last year to help them write theirs. Plagiarism is taken very seriously by the University and, if caught, both you and they will be expelled from your degree course. Would you let the following friend or relative have your essay?

The names provided in Section 1 were used to personalise the dilemmas. In an attempt to minimise any effect of order, the moral dilemma was presented first and then each subsequent page had one name per page, in random order, with the response box "yes or no". This pattern was repeated for each of the three moral dilemmas in turn for a total of 36 questions. As the affirmative response to question 1 indicates the intention *to not help* the friend or relative whereas the affirmative response to questions 2 and 3 indicates the intention *to help* the "help" response was coded as 1 in the subsequent analysis (Question 1: "No" Questions 2 and 3: "Yes") and the "not help" response as 2 (Question 1: "Yes" Questions 2 And 3: "No"). The time it took for the participant to respond to each question was timed using an applet attached to the question. Timing commenced when the participant first accessed the page and ended when they clicked to respond to the question. This method of time recording avoided any time lag associated with accessing information from or transmitting data to the server.

Results

The −2 Log Likelihood (−2LL) values for the multi-level model, split by layer, are given in Table 2 and the statistics for the best fit model for each layer are given in Table 3. The best fit model varies between layers and there is evidence for a practice effect despite the attempt to obviate this by presenting the target names in random order. Whether the target is a relative or friend is significant in the outermost two layers (Layer 2: $F=37.865$, $p<.001$, Layer 3: $F=18.718$, $p<.001$) as would be predicted by H1. However, while the b value for RorF is in the predicted direction in Layer 2 (i.e. the response time for kin was quicker than friend) it is not in Layer 3. While the inclusion of subject age (SubAge) increased the fit of our final model, it did not significantly contribute to response time in any Layer. As a consequence, H2 cannot be supported, although the negative values for b within the first two layers do suggest that, at least within these layers, the time to respond to questions tended to decrease with increasing age as H2 would predict. Sex of participant (SubSex) is a significant predictor of response time in all three layers, but the positive b values indicate that this is in the opposite direction to that predicted by H3, suggesting that male participants responded quicker than female.

The statistics for the best fit models for the data split by Layer and Response are given in Table 4. We summarise the significant results here layer by layer. For Layer 1, whether the target individual is a relative or friend is not significant regardless of the nature of response (Help: $F=0.119$, $p=.730$ Don't Help: $F=0.010$, $p=.922$). Age does

Table 2 -2LL values for multilevel linear modelling for data split by Layer (Study 1). Dependent variable: reaction time

Model	−2LL Layer 1	χ^2 change	Model	−2LL Layer 2	χ^2 change	Model	−2LL Layer 3	χ^2 change
Rank, RorF	12765.430		Rank, RorF	12343.530		Rank, RorF	10715.117	
Rank, RorF, Dilemma	12761.127	4.303	Rank, RorF, Dilemma	12325.124	18.406	Rank, RorF, Dilemma	10700.387	14.73
Rank, RorF, Dilemma, SubSex	12089.261	671.866	Rank, RorF, Dilemma, SubSex	10787.867	1537.257	Rank, RorF, Dilemma, SubSex	10204.070	496.317
Rank, RorF, Dilemma, SubSex, EC	11035.179	1054.082	Rank, RorF, Dilemma, SubSex, EC	9580.300	1207.567	Rank, RorF, Dilemma, SubSex, EC	7693.899	2510.171
Rank, RorF, Dilemma, Subsex, EC, SexRorF	11032.352	2.827	Rank, RorF, Dilemma, Subsex, EC, SexRorF	9568.461	11.839	Rank, RorF, Dilemma, Subsex, EC, SexRorF	7691.320	2.579
Rank, RorF, Dilemma, SubSex, EC, Response	10979.053	53.299	Rank, RorF, Dilemma, SubSex, EC, SexRorF, Response	9482.047	86.414	Rank, RorF, Dilemma, SubSex, EC, Response	7642.652	48.668
Rank, RorF, Dilemma, SubSex, EC, Response, SubAge	10918.598	61.455	Rank, RorF, Dilemma, SubSex, EC, SexRorF, Response, SubAge	9427.826	54.221	Rank, RorF, Dilemma, SubSex, EC, Response, SubAge	7596.084	46.568
Rank, RorF, Dilemma, SubSex, EC, Response, SubAge, RorF*SubSex	10918.370	0.228	Rank, RorF, Dilemma, SubSex, EC, SexRorF, Response, SubAge, RorF*SubSex	9427.755	0.071	Rank, RorF, Dilemma, SubSex, EC, Response, SubAge, RorF*SubSex	7596.042	0.042
Rank, RorF, Dilemma, SubSex, EC, Response, SubAge, RorF*SexRorF	10914.482	3.888	Rank, RorF, Dilemma, SubSex, EC, SexRorF, Response, SubAge, RorF*SexRorF	9403.100	24.655	Rank, RorF, Dilemma, SubSex, EC, Response, SubAge, RorF*SexRorF	7595.686	0.356
Rank, RorF, Dilemma, SubSex, EC, Response, SubAge, RorF*SexRorF, RorF*SubAge	10914.318	0.164	Rank, RorF, Dilemma, SubSex, EC, SexRorF, Response, SubAge, RorF*SexRorF, RorF*SubAge	9403.100	0	Rank, RorF, Dilemma, SubSex, EC, Response, SubAge, RorF*SubAge	7596.076	−.0390

Table 3 Statistics for the multi-level model best fit model for data split by Layer (Study 1). Dependent variable: reaction time

Variables	Layer 1				Layer 2				Layer 3			
	b	s.e.	F	p	b	s.e.	F	p	b	s.e.	F	p
Rank	−0.0882	0.0252	12.286	.000**	−0.1135	0.0186	37.241	.000**	−0.0854	0.0144	34.986	.000**
RorF	−0.1311	0.1762	0.553	.457	2.4658	0.4007	37.865	.000**	−0.3947	0.0912	18.718	.000**
Dilemma	0.7616	0.3269	5.429	.020*	0.6141	0.2345	6.857	.009*	0.4821	0.1853	6.773	.009
SubSex	0.5974	0.2550	5.490	.020*	0.7101	0.2593	7.498	.007*	0.5816	0.1876	9.606	.002
EC	−0.0387	0.0290	1.785	.182	0.0455	0.0279	2.656	.103	−0.0055	0.0210	0.069	.794
SexRorF					1.4318	0.3945	13.171	.000**				
Response	0.3160	0.1409	5.028	.025*	−0.1689	0.1335	1.600	.206	0.1834	0.0944	3.773	.052
SubAge	−0.0005	0.0024	0.053	.819	−0.0010	.0023	.171	.679	0.0004	0.0017	0.052	.821
RorF*SubSex												
RorF*SexRorF					−1.2611	.2527	24.902	.000*				
RorF*SubAge												

*$p \leq .05$; **$p \leq .001$

Table 4 Statistics for the multi-level model best fit model for the data split by Layer and Response (Study 1). Dependent variable: reaction time

	Help				Don't Help			
Variables	b	s.e.	F	p	b	s.e.	F	p
Layer 1								
Rank	−0.0431	0.0051	68.744	.000*	−0.0863	0.0452	3.644	.057
RorF	0.0375	0.1086	0.119	.730	−0.0304	0.3093	0.010	.922
Dilemma					0.8955	0.5832	2.358	.125
SubSex	0.4110	0.2025	4.121	.044*	0.9197	0.4166	4.875	.029*
EC	0.0069	0.0229	0.090	.764	−0.0761	0.0541	1.979	.160
SexRorF								
SubAge	0.0001	0.0019	0.005	.941	−0.0013	0.0038	0.110	.740
RorF*SubSex								
RorF*SexRorF								
RorF*SubAge								
Layer 2								
Rank	−0.1158	0.0216	28.842	.000*	−0.1865	0.0313	35.471	.000*
RorF	2.6614	0.4850	30.102	.000*	0.5297	0.2077	6.504	.011*
Dilemma	0.7041	0.2790	6.371	.012*	1.3624	0.3852	12.509	.000*
SubSex	0.6920	0.2558	7.315	.008*	0.7176	0.3319	4.675	.032*
EC	0.0395	0.0328	1.452	.229	0.0333	0.428	.607	.436
SexRorF								
SubAge	−0.0012	0.0021	0.329	.568	−0.0009	0.0035	0.062	.804
RorF*SubSex								
RorF*SexRorF	−1.4123	.3085	20.957	.000*				
RorF*SubAge								
Layer 3								
Rank	−0.0636	0.0173	13.599	.000*	−0.1234	0.0262	22.130	.000*
RorF	−0.8038	0.2866	7.864	.005*	−0.6661	0.1700	15.357	.000*
Dilemma	0.1890	0.2189	0.746	.388	1.0083	0.3695	7.447	.007*
SubSex	0.5326	0.1760	9.160	.003*	0.6742	0.2784	5.864	.017*
EC	0.0327	0.0195	2.769	.095	−0.0528	0.0267	2.069	.151
SexRorF	−0.7691	0.2715	8.024	.005*				
SubAge	0.0002	0.0015	0.013	.909	0.0000	0.0029	0.000	.986
RorF*SubSex								
RorF*SexRorF	0.4178	0.1948	4.601	.032*				
RorF*SubAge								

*$p \leq .05$

not have a significant impact upon response time, regardless of response. SubSex is a significant factor regardless of response with female participants taking longer to take a decision than male. For Layer 2, whether the target is a relative or a friend is significant regardless of response ("Help: F=30.102, p<001; Don't Help: F=6.504, p=.011) and b values indicate this difference is in the direction predicted by H1, i.e. response times are greater for friends than relatives. Regardless of response, Age does not have a significant impact upon response time, within Layer 2. Subject sex is significant, regardless of response, with female participants taking longer to respond than males. Finally, for Layer 3, whether the individual of focus is a relative or friend is significant regardless of response (Help: F=7.864, p=.005; Don't Help: F=15.357, p<.001) although this difference is in the opposite direction to that predicted by H1 (response time for relatives is greater than that for friends). As previously, age is not a significant factor, regardless of response. Subject sex is significant, with female participants take longer to respond than males in both cases.

Table 5 gives a schematic summary of these results. With respect to the main hypothesis, H1, the results broadly support the hypothesis within Layers 1 and 2. However, in Layer 3 the results are in the opposite direction to those predicted by H1. Age had no effect in any layer, and H2 is rejected. There were significant gender effects, but in the opposite direction to that predicted: H3, as stated, is thus not supported. Nonetheless, it is the case that females consistently spent longer than males considering their decisions, and this must carry some significance.

Discussion

The aim of this study was to test the hypothesis that participants respond quicker to moral dilemmas involving their kin than when these involve a friend, and that results will be affected by sex and age. Study 1 provides partial support for this hypothesis. There is no significant difference between the response times for relatives or friends in Layer 1, but the differences in Layers 2 and 3 are significant. While this difference is in the predicted direction in Layer 2, it is in the opposite direction in Layer 3 (i.e. response times for relatives are longer than those for friends).

Perhaps subjects do not distinguish between friends and relatives in Layer 3, despite doing so in Layer 2, because the kin which populate Layer 3 are so infrequently encountered that the participant is not comfortable with applying the schema which appears to be active in Layer 2: in other words, there is no kin premium in Layer 3. This might imply that, even though kin naming allows us to include a larger circle of individuals (i.e. the 150 layer extending out to second cousins: Dunbar 1995), kin-biased altruism extends only to the set of relationships that fall within the natural

Table 5 Summary of results for Study 1

Response*:	H1: kin<friend			H2: old<young			H3: fem<male		
	Yes	No	Total	Yes	No	Total	Yes	No	Total
Layer 1	=	=	=	=	=	=	–	–	–
Layer 2	+	+	+	=	=	=	–	–	–
Layer 3	–	–	–	=	=	=	–	–	–

* a 'yes' response implies benefiting the target individual at the expense of upholding a moral principle; +, significant in predicted direction; −, significant in opposite direction to that predicted; =, no significant difference; (−) indicates a near significant (p=0.072) negative effect

purview of biological kin selection (principally, the 50 layer, extending out to cousins). The 50-layer may thus stand as an inflexion point where one's instinctive response switches from behaving altruistically to being unwilling to compromise. If so, this suggests that individuals' willingness to behave altruistically (at least in terms of moral compromise on behalf of another) is determined more by the conventional mechanisms of kin selection than by the use of language-based kinship. Alternatively, it could be that this just happened to be the case in our pool of participants because, due to the nature of recruitment, these were overwhelmingly western college students whose experience of the extended family may be limited. Study 2 sought to check this possibility directly by controlling the recruitment of subjects.

Study 2

Since social network size increases in size with age (Hill and Dunbar 2003), the negative result in Layer 3, the outermost layer, might have been due to the fact that many of the participants in Study 1 were students, and so may have had fewer alters in this outermost layer (or, alternatively, fewer alters with whom they were familiar). A second possible confound is that the subjects in Study 1 may have included people who varied unusually widely on the individualism versus collectivism scale. To check whether these might have been confounds, we replicated the study with an older group of subjects recruited through a commercial panel provider and included a measure of collectivism-vs-individualism. We also used a wider range of moral dilemmas.

We test the same three hypotheses as in Study 1. In addition, since individuals who are high on the collectivism end of the Individualism-vs-Collectivism scale invest more in their relationships than those who are high on individualism (Singelis et al. 1995), and are more likely to act for the good of the group despite possible costs to themselves, we also hypothesise that:

> H4: Individuals who score high on collectivism will exhibit significantly faster response times than participants who score high on individualism.

Methods

Participants

Two hundred fifty six participants (128 male) were recruited via the online panel provider Qualtrics. Qualtrics were asked to recruit UK-based individuals, split equally by sex, with all participants over the age of 18 and non-students. The mean age of participants was 37.6 years (range 18–50). 91 % self-identified as White British, White Irish or White Other, 4 % as British Asian, 2 % as Black British and 2 % of mixed ethnicity.

Procedure

The procedure for Study 2 was identical to that for Study 1, with the addition of an extra measure (the INDCOL individualism-vs-collectivism index: Singelis et al. 1995), additional background questions on ethnicity, place of birth and place of residence and a wider range of moral dilemmas.

There were ten short moral dilemma questions, each with three response options (do nothing, confront them, or tell the appropriate person/authority anonymously).

The ten moral dilemma questions were:

1. You know X is having an affair: would you… [response choices]
2. You saw X selling drugs to a teenager: would you…
3. You saw X walk out of a supermarket without paying for some electrical goods: would you…
4. You know X is stealing money from their elderly employer: would you…
5. You know X is about to drive home from the pub significantly over the drink/drive limit: would you…
6. You know X is repeatedly leaving their 10 year old child at home alone: would you…
7. You know X is neglecting their dog: would you…
8. You know X is claiming sickness benefit but has a casual job: would you…
9. You know X has been banned from driving but is driving their car: would you…
10. You know X is working at the local swimming pool as a life guard but is not qualified: would you…

One personalised question and its response options was presented per page in randomised order. Each moral dilemma was presented for each friend and relative, resulting in 120 questions. Due to the number of questions, questions were presented in blocks of 10 with the option to take a break between each block. Again, response time was recorded for each question as a proxy for cognitive load.

Results

As before, the structure of the data and the possibility of a practice effect required the use of multilevel linear analysis. The variables were as in Table 1 with the exception of two additional variables representing the participant's scores for Individualism (TotalInd) and Collectivism (TotalCol) taken from the INDCOL scale. A model, with the random variable "SubjectID" at the second level, was built incorporating, in the first instance, a random intercept and, secondly, random intercept and random slope. Again the models were tested on the dataset split by Network Layer and then by both Network Layer and Response. The models investigated the main effect of relative or friend, rank, dilemma, sex of subject, EC, sex of relative or friend, response (in the first instance), subject age, TotalCol and TotalInd (all level 1 fixed variables) and the interactions between RorF and SubSex, SexRorF and SubAge on response time. The move from incorporating a random slope to a random slope plus intercept into the models indicated no improvement in model fit, so only the results pertaining to random slope are given here.

The -2LL values for the multi-level model, split by layer, are given in Table 6 and the statistics for the best fit model for each layer given in Table 7. As predicted, the tests for H1 (whether the target individual is a relative or friend) are significant in all three layers (Layer1: F=4.073, p=.044; Layer 2: F=123.838, p<.001; Layer 3: F=14.879,

Table 6 -2LL values for multi-level models with random intercept split by layer (Study 2). Dependent variable: reaction time

Model	−2LL Layer 1	χ^2 change	Model	−2LL Layer 2	χ^2 change	Model	−2LL Layer 3	χ^2 change
Rank, RorF	41078.158		Rank, RorF	38009.393		Rank, RorF	41142.682	
Rank, RorF, Dilemma	41070.677	7.481	Rank, RorF, Dilemma	37988.376	21.017	Rank, RorF, Dilemma	41141.669	1.013
Rank, RorF, Dilemma, SubSex	41070.349	0.328	Rank, RorF, Dilemma, SubSex	37988.201	0.175	Rank, RorF, SubSex	41142.530	0.152
Rank, RorF, Dilemma, EC	40055.650	1015.027	Rank, RorF, Dilemma, EC	35198.872	2789.504	Rank, RorF, EC	38950.796	2191.886
Rank, RorF, Dilemma, EC, SexRorF	40050.111	5.539	Rank, RorF, Dilemma, EC, SexRorF	35179.358	19.514	Rank, RorF, EC, SexRorF	38935.157	15.639
Rank, RorF, Dilemma, EC, SexRorF, Response	39825.612	224.499	Rank, RorF, Dilemma, EC, SexRorF, Response	35125.080	54.278	Rank, RorF, EC, SexRorF, Response	38912.409	22.748
Rank, RorF, Dilemma, EC, SexRorF, Response, SubAge	39527.553	298.059	Rank, RorF, Dilemma, EC, SexRorF, Response, SubAge	34962.951	162.129	Rank, RorF, EC, SexRorF, Response, SubAge	38739.027	173.382
Rank, RorF, Dilemma, EC, SexRorF, Response, SubAge, TotalCol	39526.513	1.04	Rank, RorF, Dilemma, EC, SexRorF, Response, SubAge, TotalCol	34962.065	.0886	Rank, RorF, EC, SexRorF, Response, SubAge, TotalCol	38736.599	2.428
Rank, RorF, Dilemma, EC, SexRorF, Response, SubAge, TotalInd	39527.260		Rank, RorF, Dilemma, EC, SexRorF, Response, SubAge, TotalInd	34962.459		Rank, RorF, EC, SexRorF, Response, SubAge, TotalInd	38738.742	0.285
Rank, RorF, Dilemma, EC, SexRorF, Response, SubAge, RorF*SubSex	39526.559		Rank, RorF, Dilemma, EC, SexRorF, Response, SubAge, RorF*SubSex	34961.704	1.247	Rank, RorF, EC, SexRorF, Response, SubAge, RorF*SubSex	38753.399	−14.372
Rank, RorF, Dilemma, EC, SexRorF, Response, SubAge, RorF*SexRorF	39518.533		Rank, RorF, Dilemma, EC, SexRorF, Response, SubAge, RorF*SexRorF	34894.952	67.999	Rank, RorF, EC, SexRorF, Response, SubAge, RorF*SexRorF	38744.823	−5.796
Rank, RorF, Dilemma, EC, SexRorF, Response, SubAge, RorF*SexRorF, RorF*SubAge	39518.305		Rank, RorF, Dilemma, EC, SexRorF, Response, SubAge, RorF*SexRorF, RorF*SubAge	34894.948	.004	Rank, RorF, EC, SexRorF, Response, SubAge, RorF*SubAge	38744.470	−5.443

Table 7 Statistics for the multi-level model best fit model for the data split by Layer (Study 2). Dependent variable: reaction time

Variables	Layer 1				Layer 2				Layer 3			
	b	s.e.	F	p	b	s.e.	F	p	b	s.e.	F	p
Rank	−.01336	.00097	368.057	.000**	−.02382	.00063	1434.256	.000**	−.02116	.00074	818.010	.000**
RorF	−.26528	.13144	4.073	.044*	1.68382	.15131	123.838	.000**	−.19551	.05069	14.879	.000**
Dilemma	−.02357	.00746	9.999	.002*	.04096	.00812	25.466	.000**				
SubSex												
EC	−.03314	.01110	.080	.777	−.02221	.01245	3.181	.075	−.02270	.01260	3.244	.072
SexRorF	−.28519	.13273	4.617	.032*	.93919	.14574	41.531	.000**	−.20025	.04958	16.313	.000**
Response	−.06791	.04298	2.497	.114	−.05904	.04409	1.793	.181	−.02996	.04686	.409	.523
SubAge	.03338	.00835	15.977	.000**	.03511	.00887	15.67	.000**	.03567	.00927	14.803	.000**
RorF*SubSex												
RorF*SexRorF	.25121	.08362	9.024	.003*	−.76406	.09246	68.287	.000**				
RorF*SubAge												

*$p \leq .05$; **$p \leq .001$

$p<.001$). However, the b values for RorF suggest that, once again, the direction of this difference is in the predicted direction (i.e. response times for friends are greater than those for relatives) only in Layer 2. Participant age (SubAge) was a significant factor in all 3 layers but the b values indicate that this was not in the direction predicted by H2 (i.e. as participants age increased, their response time increased). Sex of participant (SubSex) was not a factor in the best fit model for any of the layers, leading us to reject H3. Finally, TotalInd and TotalCol were not significant factors in the best fit model for any Layer: H4 was not supported.

The statistics for the best fit models for the data split by layer and response are given in Table 8. Again, we summarise the results layer by layer. For Layer 1, whether the target individual is a relative or friend is not significant regardless of the nature of the response. Age is a significant factor for all three response types, with b values indicating that, for all response types, response times increase as age increases. Subject sex is not a factor in the best fit model regardless of response. Neither TotalInd nor TotalCol are factors within the best fit model for any response. For Layer 2, whether the target individual is a relative or a friend is significant regardless of response (Do nothing: $F=34.971$, $p<.001$; Confront: $F=76.209$, $p<.001$; Tell: $F=16.059$, $p<.001$); b values indicate this difference is in the direction predicted by H1 (i.e. response time for friends is greater than that for relatives). Age has a significant impact upon response time if the response is to do nothing or to confront, but not if the response is to tell. b values indicate again that as age increases, time to respond increases. Sex is, again, not a factor in the best fit model, regardless of response type. TotalInd and TotalCol are not factors in the best fit models for any response type. Finally, for Layer 3, whether the target individual is a relative or friend is significant only if the response is to tell ($F=6.994$, $p=.009$), although this difference is in the opposite direction to that predicted by H1: response time is greater for relatives than friends. Age is only a factor if the response is to confront. Here, there is a significant effect of participant age but not in the direction predicted by H2: as age increases response time increases. Neither Sex, TotalInd nor TotalCol are factors in any best fit model.

Table 9 provides a schematic summary of these results. As in Study 1, H1 is supported in respect of Layer 2, but not Layers 1 or 3. H2 is rejected, but there are significant *negative* effects due to age in Layers 1 and 2: in these cases, contrary to the prediction, older subjects are significantly slower than younger ones. H3 is not supported in any layer: sex of participant has no effect. Finally, there is no evidence that individualism vs collectivism has an effect: H4 is rejected.

Discussion

The results for Study 2 replicate, in part, those for Study 1, but suggest that the picture in Layer 3 may be complicated by the nature of the decision taken. There is a significant difference between the response times for relative versus friend in Layer 1 in favour of friends but any significance disappears when the nature of the response is taken into consideration. For Layer 2, the difference is in the direction predicted by H1. But for Layer 3, there is a significant difference for the response "Tell", but in the opposite direction to that predicted by H1. Gender had no significant effect in any layer, and the effect of age was, if anything, in the opposite direction to that predicted (younger subjects were faster than older ones, at least in Layers 1 and 2). Hence,

Table 8 Statistics for the multi-level model best fit models for the data split by Layer and Response (Study 2). Dependent variable: reaction time

Variables	Do Nothing				Confront				Tell			
	b	s.e.	F	p	b	s.e.	F	p	b	s.e.	F	P
Layer 1												
Rank	−.01087	.00214	25.788	.000**	−.01395	.00083	282.309	.000**	−.01632	.00149	119.472	.000**
RorF	.05791	.13244	.191	.662	.01063	.07005	.023	.879	−.38432	.29364	1.713	.191
Dilemma					−.02280	.00886	6.630	.010*				
SubSex												
EC	.01272	.02714	.220	.639	−.00272	.01379	.039	.844	−.01102	.02271	.235	.628
SexRorF									−.36091	.26990	1.478	.224
SubAge	.03134	.01260	6.183	.014*	.03627	.00872	17.310	.000**	.03297	.01187	7.715	.006*
RorF*SubSex												
RorF*SexRorF					.07494	.03260	5.285	.022*	.37362	.18578	4.045	.045*
RorF*SubAge												
Layer 2												
Rank	−.02189	.00144	231.837	.000**	−.02349	.00077	932.979	.000**	−.02461	.00164	226.084	.000**
RorF	2.11896	.00144	34.971	.000**	1.61118	.18456	76.209	.000**	.50479	.12597	16.059	.000**
Dilemma					.04151	.00979	17.969	.000**				
SubSex												
EC	.00466	.02796	.028	.868	−.00780	.01502	.269	.604	−.06121	.02883	4.508	.034*
SexRorF	1.18382	.35707	10.992	.001*	.94640	.17638	28.791	.000**				
SubAge	.03711	.01284	8.354	.004*	.03876	.00910	18.153	.000**	.02567	.01330	3.722	.056
RorF*SubSex												
RorF*SexRorF	−1.02092	.22134	21.275	.000**	−.73093	.11235	42.325	.000**				
RorF*SubAge												

Table 8 (continued)

Variables	Do Nothing				Confront				Tell			
	b	s.e.	F	p	b	s.e.	F	p	b	s.e.	F	P
Layer 3												
Rank	−.10686	.00167	102.086	.000**	−.02343	.00095	610.068	.000**	−.01940	.00191	102.811	.000**
RorF	.00287	.11493	.001	.980	.245616	.19869	1.528	.216	−.83559	.31595	6.994	.009*
Dilemma												
SubSex												
EC	.00259	.02619	.010	.921	−.04919	.01611	9.321	.002*	.01328	.02926	.206	.650
SexRorF	−.35894	.11315	10.063	.002*	.33713	.19558	2.971	.085				
SubAge					.04112	.00946	18.906	.000**				
RorF*SubSex												
RorF*SexRorF					−.35892	.12492	8.255	.004*				
RorF*SubAge									.01846	.00773	5.706	.018*

*$p \leq .05$; **$p \leq .001$

Table 9 Summary of results for Study 2

Response*:	H1: kin<friend			H2: old<young			H3: fem<male			H4: Indiv<Collect		
	Yes	No	Total	Yes	No	Total	Yes	No	Total	Yes	No	Total
Layer 1	=	=	–	–	–	–	=	=	=	=	=	=
Layer 2	+	+	+	–	−§/=	–	=	=	=	=	=	=
Layer 3	=	-§/=	–	=	−§/=	–	=	=	=	=	=	=

*a 'yes' response implies benefiting the target individual at the expense of upholding a moral principle; the 'no' response includes both 'confront' and 'tell' responses; § for confront only; +, significant in predicted direction; −, significant in opposite direction to that predicted; =, no significant difference

despite using a non-student population, friends and relatives in Layer 3 appear to be processed in a similar manner where the decision is taken to help, but kin take significantly longer to process when help is refused. Further, including a measure of innate prosociality, the INDCOL, did not improve our model: neither TotalInd nor TotalCol were included in the best fit model for any Layer. Prosociality is, of course, notoriously difficult to assess, and it may be that the index we used is not the most suitable. Nonetheless, subject to this caveat, it seems that our initial results were not confounded by individual differences in prosociality.

General Discussion

The aim of this study was to test the hypothesis, derived from Brashears' (2013) studies of kinship as a cognitive schema, that kin naming systems evolved to provide a cognitively less demanding mechanism for processing decisions. We hypothesised that kin naming evolved to reduce the cognitive load of maintaining relationships. By enabling savings to be made in the costs of relationship maintenance, individuals may be able to manage a larger social network, thus explaining how humans have been able to increase their social community size from the limit of 50 observed in primates to the 150 observed in modern humans.

The results from our two studies allow us to draw three main conclusions. First, there was no difference in response times on decisions for kin versus friends in Layer 1 (the 15 layer, or sympathy group) in either study; friends and relatives thus appear to be treated equally within the sympathy group, at least with respect to processing time if not the nature of the decision. This might lend some support to the suggestion that close friendship resembles kinship (Ackerman et al. 2007). Second, in both studies, moral dilemmas were processed faster for a nominated relative than for a friend in the second layer (the affinity group, equivalent to the outer layer for nonhuman primates). To this extent, savings on the cognitive load of relationship maintenance in this layer might allow some additional relationships to be maintained in the 150 layer, especially given that the time investment cost of kin relationships in the outermost layer is close to nil (Dunbar et al. 2014). Nonetheless, third, moral decisions were not processed faster for kin in the outermost layer (the 150 layer, or active network); indeed, to some extent the reverse was actually the case, at least in respect of all decisions in Study 1 and 'no' decisions in Study 2. Study 2 demonstrated that this result was not a confound due either to the ages or status of the subjects in Study 1 or to individual differences in prosociality (as indexed by the individualism/collectivism scale).

There are two possible explanations for this counterintuitive finding. One is that people genuinely don't distinguish between distant friends and distant relatives in the outermost layer, and the schema is only active at all in the first two layers. However, our analysis in Study 2 of the impact that nature of response has upon the response time in Layer 3 suggests an alternative possibility – that the schema *is* active in this layer but is being consciously overridden when a participant is considering acting negatively towards the target (either refusing to help or reporting a kin member to the authorities). The need to weigh up the consequences of refusing to help a relative results in response times being higher for kin than friends in this layer. One likely reason for this is that the embeddedness of the kin network means that participants need to consider the potential for repercussions from the wider kin network if they refuse help to a relative. Further, the higher response time for kin in Study 1 and the lack of difference in response times in Study 2 when the response is "to help" may be because participants have so little contact with these individuals that they have to consciously consider their response. Testing this hypothesis would require a rather different experimental design than the one we used here but would be a useful next step.

Brashears (2013) concluded that kin naming allowed for savings in terms of cognitive processing and hence facilitated the resultant expansion of the social network. However, he only considered networks of 15 individuals (i.e. our Layer 1), and hence limited his experiment to close kin (parents, siblings, etc.). Our results confirm that his schema effect extends out to the next layer of the network (the 50-layer, Layer 2 in this study), but not to Layer 3 (the full 150-layer) where processing costs *increase* for kin.

We checked for the potentially confounding effects of gender and age, but found only limited evidence for these being an issue: gender (but not age) had a significant effect in Study 1, but the reverse was true in Study 2, possibly suggesting that whether or not men and women process dilemma decisions differently may be sensitive to the nature of the dilemma. The positive b values for subject sex in Study 1 indicate that men were responding quicker on the dilemmas than women, in contrast to the prediction of H3. This seems to contrast with previous work suggesting that women are more adept at accessing and using information relating to social contexts and exhibit greater recall of their kin network (Goddard et al. 1998; Salmon and Daly 1996; Sehulster 1995). However, in contrast to all these studies, which used simple recall tasks, we used a moral dilemma task with no recall component. One possible explanation for our gender results is that the slower responses by women are due to the fact that they consider the consequences of their actions more carefully than men do precisely because they are more attuned to the complexities of the kin network. Such a possibility is supported by recent work which found that, when taking moral decisions, men do so via a set of prescribed, societal rules while women take into account the emotional impact of their decision on a case-by-case basis (Friesdorf et al. 2015). Refusing to assist someone could have more far reaching consequences within the family community than saying 'yes', and women may be more sensitive to this. Salmon and Daly (1996) reported that women request more assistance from their kin, and in particular their female kin, than men do, suggesting that the consequence of refusing to help kin may have greater repercussions for women than for men. It may be that women, regardless of the presence of a schema, take more aspects of a relationship into account when making their decisions, whereas men more typically respond on absolutist grounds, leading to longer response times in women. This is reminiscent of the fact that women make more complex decisions than men do when evaluating potential romantic partners (Buss 1989; Waynforth and Dunbar 1995; Pawłowski and Dunbar 1999).

Age also produced somewhat mixed results. In Study 1, subject age did not significantly contribute to response times. In contrast, in Study 2, age of subject was significant in all three layers but the positive b values suggest that, as age increases, so response times also increase, contrary to the prediction of H2. On balance, age is, thus, also unlikely to account for the positive results we found in respect of the main results, at least in so far as learning and experience effects are concerned. It might be that older individuals take longer in making decisions because they evaluate the wider consequences of their actions more carefully than younger people do, or that they are more willing to compromise on their moral principles, at least in respect of friends and family. Either way, including gender and age within the statistical models means that we can rule these out as possible confounds for the main findings.

Our study was, of course, restricted to data from Western English-speaking populations. For an evolutionary explanation for kin naming to be robust it must provide a universal explanation across cultures. Although there is a well known degree of variation in kinship naming across cultures, in fact there are only seven major variants and there is broad underlying agreement in how these label individuals in a pedigree (Cronk and Gerkey 2010). However, for present purposes, it should be noted that it is not the nature of the kin naming system that is linked to the reduction in cognitive load but the mere existence of the understanding that people in one's network can be categorised into kin and non-kin, irrespective of how these are defined, and that this labelling is purely linguistic. In small scale traditional societies, almost everyone in the local community will be related to each other directly or indirectly by marriage (so-called "universal kinship": Barnard 1978, 2008). Pedigree models with exogamy show that the community sizes of ~150 that typify natural communities of this kind in fact represent the combined living descendants of an apical pair of great-great-grandparents for the current offspring generation (Dunbar 1995). Indeed, no known kinship naming system has kinship terms for any individual that lies beyond this pedigree layer. Our argument should provide an explanation for the emergence of kin naming regardless of the particular kin naming system in place, and we see no intrinsic reason why the details of the kinship naming system should make any difference.

In traditional small scale societies, kinship labelling is, of course, used for many important purposes, including specifying categories of marriageable individuals (Walker et al. 2011) and managing normative kin-based altruism (Curry et al. 2013; Jones 2000). Our concern has not been so much with the functions of kin labelling as such as with its cognitive underpinnings. Our findings are thus compatible with any functional purposes that require kinship naming. Following Brashears (2013), we have focussed on the possibility that kinship naming reduced the costs of processing social decisions, and thereby allowed humans to increase the size of their communities. While our findings broadly confirm Brashears' findings for close kin, our results go beyond his in suggesting that this schema effect works efficiently only within the confines of close family. It does not seem to apply to extended kinship circles (Layer 3), where kinship seems, if anything, to *add* significant cognitive load because we have to evaluate the consequences that our actions might have round the wider kin network.

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