Ecological knowledge increases throughout childhood in Pemba, Tanzania: Exploring drivers of variation.

Ilaria Pretelli[1], Monique Borgerhoff Mulder[1], Richard McElreath[1]

[1]Max Planck Institute for Evolutionary Anthropology, Leipzig

5371 words

February 25, 2022

Abstract

Humans live in diverse, complex niches where survival and reproduction are conditional on the acquisition of knowledge. Humans also have long childhoods, spending more than a decade before they become net producers. Whether the time needed to learn has been a selective force in the evolution of long human childhood is unclear, because there is little comparative data on the growth of ecological knowledge throughout childhood. We measured ecological knowledge at different ages in Pemba, Zanzibar (TZ), interviewing 93 children and teenagers between 4 and 26 years. We developed Bayesian latent-knowledge models to estimate individual knowledge and its association with age, activities, household family structure, and education. In the studied population, children learn during the whole pre-reproductive period, but at varying rate, with fastest increases in young children. Sex differences appear during middle childhood and are mediated by participation in different activities. In addition to providing a detailed empirical investigation of the relationship between knowledge acquisition and childhood, this study develops and documents computational improvements to the modeling of knowledge development.

1 Introduction

Humans have a distinct pattern to their life history, even compared to other apes. We require adult provisioning for a long period of time, which constitutes childhood (Bock & Sellen, 2002; Bogin, 1997; Leigh, 2002). The emergence of this phase in our lineage has been connected to other specifically human traits, including early weaning, short inter birth intervals, cooperative breeding and the presence of multiple dependent offspring in a family (Bogin, 1997; Kaplan, 1996; Kramer, 2005, 2010, 2011; Kramer & Ellison, 2010). It is theorized that this period is important for acquiring skills and knowledge, which are necessary to exploit our species' complex niche (Kaplan, Bock, & Hooper, 2015; Kaplan, Hill, Lancaster, & Hurtado, 2000; Robson & Kaplan, 2003; Schuppli, Isler, & Van Schaik, 2012). The connection between life history, knowledge and the prevalence in our niche of nutrient-dense, difficult-to-acquire food resources has been extensively explored in Kaplan et al. (2000). Individuals who postponed reproduction in order to improve their understanding of the environment and increase their ability to extract its resources were selected through the benefits reaped in adulthood, when overproduction could support dependent offspring (Hill & Kaplan, 1999).

Schuppli, Graber, Isler, and van Schaik (2016) present a comparative analysis supporting this hypothesis, as they show that niche complexity correlates with adult provisioning and lengthy development in carnivora and primates respectively. But testing this hypothesis in our species is difficult. Previous research focused on describing age specific patterns of foraging efficiency (Bird & Bird, 2005; Bird & Bliege Bird, 2002; Bliege Bird & Bird, 2002; Blurton Jones & Marlowe, 2002; Bock, 2002; Crittenden, Conklin-Brittain, Zes, Schoeninger, & Marlowe, 2013; Gurven, Kaplan, & Gutierrez, 2006; Koster et al., 2020), or knowledge (Koster, Bruno, & Burns, 2016; Schniter et al., 2021). But the level of modelling detail reserved to somatic and cerebral growth (González-Forero, Faulwasser, & Lehmann, 2017; Kuzawa et al., 2014) has not extended to knowledge acquisition.

Human bodies grow slowly, but our brains grow quickly. A ten year old child's brain has already reached its adult size, before the reproductive tissues start to develop and long before somatic growth is completed (see dashed lines in figure 1, adapted from Bogin, 1997). Children's bodies increase slowest around the time that the brain is adult in size, but not yet completely adult in structure. What are the evolutionary origins of this pattern, and how does it relate to what the brain is doing at each age?

Unfortunately, we don't know with much precision how knowledge and skill maps onto changes in brain and body structure. Does knowledge increase track cerebral growth (e.g. green curve in figure 1), as it would be expected if the only condition necessary for the acquisition of knowledge was brain development? Or is knowledge simply a prerequisite to reproduce and it can be acquired in a short time, so that it increases just before individuals reach sexual maturity (purple curve, figure 1)? Previous studies report a slow, long period of knowledge acquisition, inconsistent with the aforementioned explanations, but as yet we do not have a clear understanding of how learning is patterned. Ascertaining the shape of knowledge acquisition can give insights on its role for the

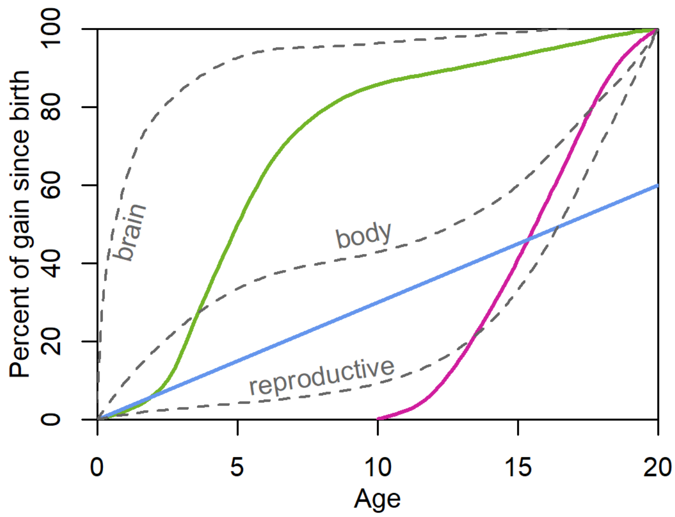

Figure 1: Growth curves for different body tissues in dashed grey lines, adapted from Bogin (1997), with overlaying possible growth curves for knowledge, continuous lines. If learning rates were dependent exclusively on brain size, we could expect knowledge to follow the trajectory of the green curve. On the contrary, if knowledge was a pre-requisite for reproduction, and could be acquired in a short periods of time, it could simply increase before sexual maturity, as described by the purple curve. Finally, the blue line shows a slow increase of knowledge with age, potentially continuing even after sexual maturity, which is consistent with the hypothesis that learning requires time, although there is no proof that knowledge should grow linearly.

evolution of childhood.

In this paper, we focus on the acquisition of ecological knowledge because of its potential association with fitness, for example through increased returns when foraging (Koster et al., 2016; Reyes-Garcia et al., 2016) or health benefits (McDade et al., 2007; Reyes-García et al., 2008). We make three specific contributions to our understanding of how knowledge is acquired.

First, we develop a novel analysis of knowledge using Item Response Theory (Osteen, 2010). We model knowledge as a latent variable measured with several independent survey tools. This method also allows for the inference of different dimensions of knowledge, which allow to identify gender-specific patterns of learning. It simultaneously measures the reliability of different survey approaches.

Second, we describe in detail the variation in knowledge dependent on age and sex. Concerning age, we focus on a sample ranging from 5-26 years, and we allow the relational function between age and knowledge to emerge from the data. This is in contrast to previous studies, which impose linear or logistic functions and focus on adults (Bortolotto, de Mello Amorozo, Neto, Oldeland, and Damasceno-Junior (2015) 21-86 years, Geng, Zhang, Ranjitkar, Huai, and Wang (2016) 21-91 years, Koster et al. (2016) 10-80 years, with few individuals below 15; Schniter et al. (2021) 5 to 86 years, only 7 individuals below 30), or divide children in large age categories (Cruz-garcia et al. (2018) children 7-14 divided in two categories; Quinlan, Quinlan, Council, and Roulette (2016) children from 4 to 17 years divided in three categories; Gallois, Duda, and Reyes-García (2017) divides only between children and adults). This allows us to explore the relation between age and knowledge in the most important phases of our development with more precision, in an attempt to understand how knowledge acquisition maps onto other life history traits. Following the assumption that labor division along gender lines entails knowledge specializations, we also investigate sex differences in ecological knowledge. Previous studies provide contrasting results on whether boys and girls differ in their levels of ecological knowledge (Blacutt-Rivero, Moraes R., Gruca, & Balslev, 2016; Cruz-garcia et al., 2018; Gallois et al., 2017; Geng et al., 2016; Schniter et al., 2021; Setalaphruk & Price, 2007). Here we find evidence of gender-specific dimensions of knowledge, rather than differences in overall levels of knowledge.

Third, we supplement our description of variation in the pattern of knowledge acquisition with a causal analysis of the factors influencing this variation. We focus on three specific factors: first, exposure and practice (gendered-activities effects); second, access to adult experts or peers (household and family composition effects), and third opportunities for learning (formal education effects). These were chosen because they were expected to represent opportunities for learning through practice or exposure to models of behavior in the particular ethnographic context. Our specific contribution in the context of exposure and practice is to show how gendered differences in knowledge are related to the differential engagement in sex specific activities in different subsets of the ecological niche, consistent with expectations that such differences are not necessarily innate. Household composition is leveraged to identify how adult experts or peers (Boyette, 2013; Lew-Levy, Reckin, Lavi, Cristóbal-Azkarate, & Ellis-Davies, 2017; Ohmagari & Berkes, 1997; Page et al., 2021; Ruddle, 1993), in addition to parents (Hewlett & Cavalli-Sforza, 1986; Lozada, Ladio, & Weigandt, 2006), might influence the acquisition of knowledge about the local environment. Similarly, we examine the effects on knowledge acquisition of birth order (Quinlan et al., 2016), to determine whether late-borns gain more access to older sibling role models, and/or early-borns enjoy preferential access to parental and grandparental wisdom. Finally, participation in formal education can lower exposure to locally relevant ecological knowledge, as time invested in school attendance could reduce opportunities for acquiring information about the environment (Quinlan et al., 2016; Reyes-García et al., 2010).

2 Materials and Methods

2.1 Research location

The data used for this study were collected in a village close to the forest of Ngezi, on Pemba, the northern island of the Zanzibar archipelago, a semi-autonomous zone of Tanzania (see figure 2). Pemba is part of the Swahili world, with multiple historical and cultural influences: first the Bantu expansion from the mainland, then 700 years of trade in the Indian ocean, and later Portuguese, Omani and British colonial power (Fleisher et al., 2015; LaViolette & Fleisher, 2009). Especially important has been the influence of the Arab world and Islam, since at least the eleventh century and then during the rule of the Omani Sultanate, which was weakened by the British at the end of the 19th century, but formally deposed only in 1963 (Fleisher & La Violette, 2013).

The island, located just below the equator (5S), enjoys a tropical climate and mild seasonality, with an alternation between drier and rainier seasons following the monsoon cycle. Its densely distributed population ($428/km^2$, about twice as high as Switzerland) mostly lives in rural areas (around 80%, according to the National Bureau of Statistics Ministry of Finance, Statistician, Ministry of State Presidents Office, & Good Governance, 2014) and depends largely on agriculture, fishing and other forest based activities (Andrews & Borgerhoff Mulder, 2022; Zahor Zahor, 2021).

The forest of Ngezi is the largest remaining patch of rain forest in Pemba, and the people living around it depend on terrestrial and maritime habitats for more than 80% of their livelihoods. Most of the income of the typical household in the area around Ngezi comes either from fishing (9.7%), agriculture (farming 20.6%, livestock 3.9%, agroforestry 4.2%, 11.9% clove production, which is the main cash crop on the island) or the forest itself (forest products, mainly firewood, for 33% of total income for the average family in the area around Ngezi forest, according to Andrews and Borgerhoff Mulder (2022)). Hunting is relatively rare among the adult population, in large part because of the scarce wildlife of reasonable size, but still present in many areas of the island (Walsh, 2007).

Children comprise a large part of the growing population of Pemba, where 48% of inhabitants are below 15 years of age (National Bureau of Statistics Ministry of Finance et al., 2014). Young people

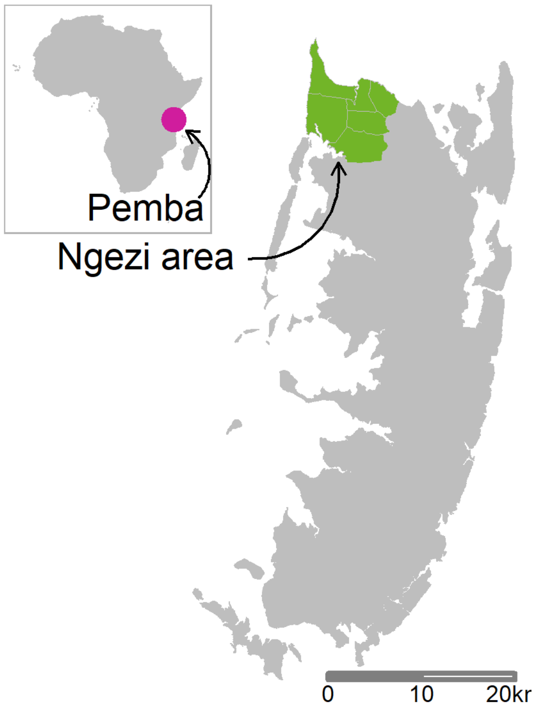

Figure 2: Pemba lies offshore Tanzania. The *sheihas* - administrative units - in the northwestern peninsula, colored in green, are still partially covered by the forest of Ngezi.

divide their time between domestic and farming chores, education at both the state and Koranic schools and play. There is variability in the extent to which children and teenagers interact with the natural environment, mainly when they forage, depending on personal inclination and their familial or environmental conditions. Children gather shellfish and other invertebrates on the shores fringing the mangrove forest, or hunt birds in the forest.

2.2 Data collection

Village census: With government approval for research (IMMZ/07/17/25, ethic approval provided also by Max Planck Institute Ethics Council, application number 2019_05), IP visited all households in the village between June and August 2019. The objective of this survey was to record a full village census with relevant household level characteristics, so that background variables on subjects (opportunistically sampled, see below) were known. The survey also provided the opportunity to introduce the project to the full community, and to obtain approval for future interviews with the children.

Knowledge interviews: Using an opportunistic sampling procedure - effectively children and young adults volunteering for interview - IP conducted a survey instrument measuring knowledge of the natural environment (as defined in Supplementary section 9.1); the extent and impact of any sampling bias that could have arisen from this procedure is examined in Supplementary section 9.2. In sum, 93 individuals between 5 and 26 years of age participated in the knowledge interviews. These consisted of three different types of questions, namely: (i) freelisting questions (Quinlan, 2005), in which children were asked to name all the living creatures (*viumbe*, which include plants, different kinds of animals and also spirits that are thought to inhabit nature) found in the village/cultivated fields, in the forest or in the sea. The named items were then checked for misspelling, and then again with local and international collaborators to ensure appropriate identification of the answered items; (ii) a list of 50 multiple choice quiz questions probing different aspects of ecological knowledge, each

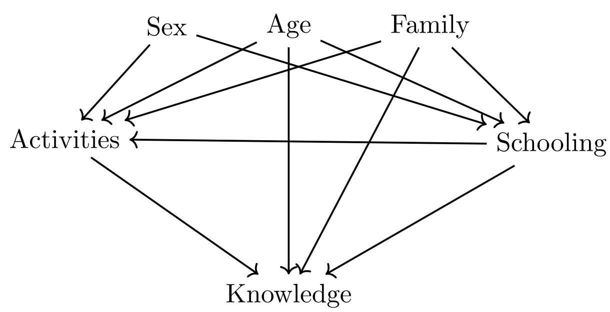

Figure 3: DAG describing relationships between analyzed variables.

with two options, developed with the help of both the Department of Forestry and Non Renewable Natural Resources (DFNRNR) and focus groups with adults in the village; (iii) a task of image recognition using pictures collected around the village or elsewhere in Pemba, in which children were asked to name all the living beings appearing in a sequence of 27 photographs. Answers given to each picture were rated as acceptable or non-acceptable during a focus group with adults in the village following data collection. More details on the interviews and data can be found in Supplementary section 9.4.

2.3 Causal framework

Data collection and analysis were informed by preliminary work aimed at describing the causal and non-causal factors influencing the association between age and knowledge. Specifically, we described all the aspects of individuals that are expected to influence knowledge in a Direct Acyclic Graph (DAG) and later in a full structural causal model that we used to validate the analysis code (see figure 3 and Supplementary section 9.5). A DAG is a heuristic generative model that allows derivation of a causal estimand (Pearl, 1995). Each causal query may require a different statistical procedure that includes different variables.

We relied on the DAG described above to plan data collection, so that all the variables would be recorded, as well as to define the analyses described below. The analysis can be divided in a descriptive and a causal section. The first illustrates how knowledge changes with age; the causal section, instead, describes the effect of sex, activities, family and schooling on the development of knowledge.

Of course it is possible that unobserved confounds exist along any edge in our DAG. We encourage the perspective that any estimated effects are possibly partially due to such confounding. This is true in all observational, anthropological investigations. The additional transparency of our approach, and its ability to logically derive statistical procedures from causal assumptions, is its strength.

2.4 Analysis

We developed multiple Bayesian models targeting our different inference goals, each composed of two different parts. The core of the models is an Item Response Theory (IRT) model. IRT models, initially developed as a mean to grade tests in pedagogy (Osteen, 2010), aim at estimating one or multiple latent traits, such as individual knowledge (K_i), from answers to questions while simultaneously allowing questions to vary in difficulty (b_j) and discrimination (a_j, i.e. how helpful they are at discriminating between high and low knowledge individuals). So for each question j, an individual i has a probability p of answering correctly $Y_{i,j} = 1$ (see equation 1 and 2); that is, naming a specific item in the freelist, answering correctly an item in the quiz, or recognizing an item in the image recognition task. The quiz questions differ from the other two types because the correct answer can be given simply by guessing, and thus required a 3PL IRT model, which includes a pseudo-guessing parameter c_j (Osteen, 2010). All three types of data contribute to the estimation of one single measure of knowledge for each individual (see Supplementary section 9.6 for an extended description of the model's functioning and implications).

$$Y_{i,j} \sim \text{Bernoulli}(p_{i,j}) \tag{1}$$

$$\text{logit}(p_{i,j}) = a_j(K_i - b_j) \tag{2}$$

The knowledge K_i in the IRT part of the model is simultaneously used as a dependent variable in the second part of the model, which estimates the effect of various factors on individual knowledge. Age is included in all models as an ordered categorical variable, so that there is a sex specific maximum effect for age β_s (for sex s) and each year adds a proportion δ_y of the total effect. This means that, while we impose monotonicity on the function relating age to knowledge (knowledge never decreases with age), the curve of the relation between knowledge and age emerges from the data themselves, rather than being imposed to be a specific function in the model design. Model 1, described by equation 3, includes varying random effects α_i for individuals in addition to this sex and age specific estimate, and can hence tell us the total effect of age and sex combined.

$$K_i = \omega + \alpha_i \sigma_\alpha + \beta_s \sum_{y=1}^{Age_i} \delta_y \tag{3}$$

The full version of this model is a compensatory Multidimensional IRT model (Reckase, 2009), that allows different dimensions of knowledge to emerge from the data. This is aimed at determining whether the individuals in our sample are experts in certain aspects of the environment, while having lower knowledge in others; in other words if there is knowledge specialization. The probability individual i has of answering a single question j correctly is the sum of multiple probabilities for each dimension d, and individuals are assigned a measure of knowledge in each dimension $K_{i,d}$. This approach allows us to partition the variation among knowledge of individuals in any number of dimensions, see Supplementary equations 3 and 4, and Supplementary section 9.8.

The results of this first model above are descriptive. The relationship between age and knowledge is not really a causal relationship, because any association between age and knowledge is presumably a result of accumulated experience and instruction, not merely of calendar age.

In contrast, the models described below aim instead at estimating the causal effect of the other factors included in the DAG in figure 3. In order, model 2 (equation 4) includes also household level varying random effects η_h and effects of each of the ten possible activities γ_{act} on individual knowledge (see Supplementary section 9.3.2 for a description of these activities). Model 3 (equation 5) estimates the effect of co-residing with either parent for individuals of both sexes (ψ_s is the sex specific effect of being in the same household with mothers, ϕ_s with fathers). Further models to test the effect of other factors such as schooling and birth order are described in Supplementary section 9.6.

$$K_i = \omega + \alpha_i \sigma_\alpha + \eta_h \sigma_\eta + \beta_s \sum_{y=1}^{Age_i} \delta_y + \sum_{act=1}^{10} \gamma_{act} \text{Activity}_{i,act} \tag{4}$$

$$K_i = \omega + \alpha_i \sigma_\alpha + \eta_h \sigma_\eta + \beta_s \sum_{y=1}^{Age_i} \delta_y + \psi_s \text{Mother}_i + \phi_s \text{Father}_i \tag{5}$$

We determined priors for all models through prior predictive simulation. The resulting priors are weakly informative, specifying low probability for impossible outcomes and inducing regularized estimates, but allowing a very wide range of results. The priors used for the model are:

$$\begin{aligned}
a_j &\sim \text{Half-Normal}(0,1) \\
b_j &\sim \text{Normal}(0,2) \\
\omega &\sim \text{Normal}(-5,3) \\
\beta_s &\sim \text{Folded-Normal}(3,1,0) \\
\delta_y &\sim \text{Dirichlet}(0.5) \\
\sigma_\alpha, \sigma_\eta &\sim \text{Exponential}(1) \\
\alpha_i, \eta_h, \gamma_{act}, \phi_s, \psi_s &\sim \text{Normal}(0,1)
\end{aligned}$$

The prior for a, a normal distribution limited to positive values, ensures that more knowledgeable individuals have higher values than less knowledgeable ones. The slightly less constrained prior for b allows the axis of the latent knowledge to expand to accommodate all the values for each question (to see what happens when changing the priors for b, see figure S9). Note that the individual knowledge measures K_i do not require a prior distribution, but are informed by the combination of the priors for a and b. For the parameters α_i, η_h, σ_α, σ_η, δ_y, γ_{act}, ψ_s, and ϕ_s weakly informative regularizing priors have been used. The priors for the parameters ω and β_s, instead, have been chosen to allow the function to expand in the negative space where the values of knowledge are placed by the IRT model.

We estimated the posterior distribution for each model using the Hamiltonian Monte Carlo engine Stan (Stan Development Team, 2021b), specifically CmdStan (Stan Development Team, 2021a). Posterior distributions were processed in R 4.1.0 (R Core Team, 2021), with the help of the Statistical Rethinking R package, version 2.13 (McElreath, 2020). For all analyses, visual inspection of traceplots, Gelman-Rubin diagnostic and effective number of samples indicate model convergence.

Parameters estimation in the Bayesian framework does not return point estimates, but rather a posterior distribution of possible values for a parameter. The figures in the result section reflect this feature, e.g. each line in figure 4 is draw by a set of values sampled from the posterior distribution of parameters. Finally, prior to fitting to real data, all models have been tested with simulated data, as described in Supplementary section 9.7. This allowed to ensure that the models could recover 'real' parameter values. Simulation code as well as all the other code necessary to reproduce these analyses is available on GitHub (https://github.com/lalla-ilaria/Children_eco_knowledge).

2.5 Results

2.5.1 Descriptive results

In agreement with previous studies, knowledge in our model increases along all sampled ages. The lines in figure 4 show the estimated increase in knowledge per each year of age, plotted over the dots representing individual measures of knowledge resulting from the IRT part of the model. Knowledge increases quite steeply during early and middle childhood, keeps increasing during most of adolescence and then starts leveling off around 20 years of age. Age-specific effects, shown in figure S7, are largest for ages 7 and 11, suggesting that the time around these years has higher importance for knowledge than, for example, ages 20-25 (see Supplementary section 9.3.1 for reasons why we are confident in our age estimations).

Sex differences in ecological knowledge, as identified from the one dimensional model, are clearly visible in Figure 4. This difference appears during the juvenile period, between 7 and 12 years, right when division of labor begins to emerge, and results in higher undifferentiated ecological knowledge among the oldest boys in our sample when compared to the oldest girls. But this one dimensional description of knowledge does not tell the whole story. When we partition knowledge into more than one dimension (see section 2.4 in Methods), three main dimensions emerge (figure 5). In the first, both sexes acquire knowledge at a similar rate, plausibly representing general knowledge. In the second, there is a sharp increase in knowledge among boys, and no age effect among girls, which probably reflects a male-specific dimension of knowledge. Finally a third dimension capture remaining variation, which contains no strong sex differences. Supplementary section 9.8 explains why we think three dimensions are the best description of the data.

2.5.2 Causal results

We attempted to estimate the causal influence of activities, household family structure, and school attendance on knowledge. In each case, we try to control for unmeasured household-level variables, using random effects. This is because any correlation caused by some social characteristic associated to specific households can induce spurious correlations between the outcome variable, Knowledge, and the other variables that stay in the path of Family (see DAG in figure 3). The posterior estimates for these random effects suggest that not much knowledge variation is due to differences between the families (see Supplementary section 9.9). However, the models are not designed to estimate

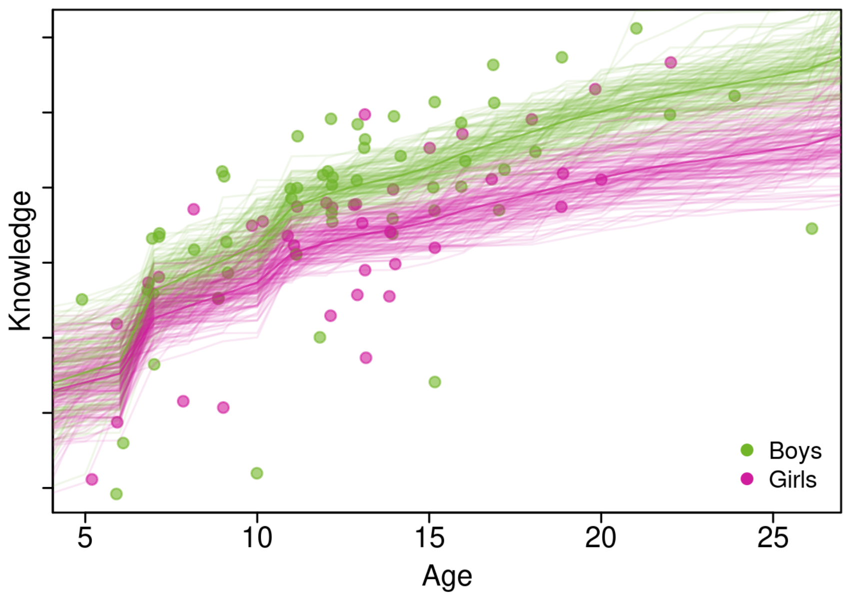

Figure 4: The points in the figure represent individual knowledge K_i as measured by the IRT model, color coded for sex. The average knowledge for an individual of a certain age and sex, as predicted by model 1 in equation 3, is represented by the continuous lines, where the darker one is the mean of the distribution, and the lighter lines represent 150 draws from the posterior.

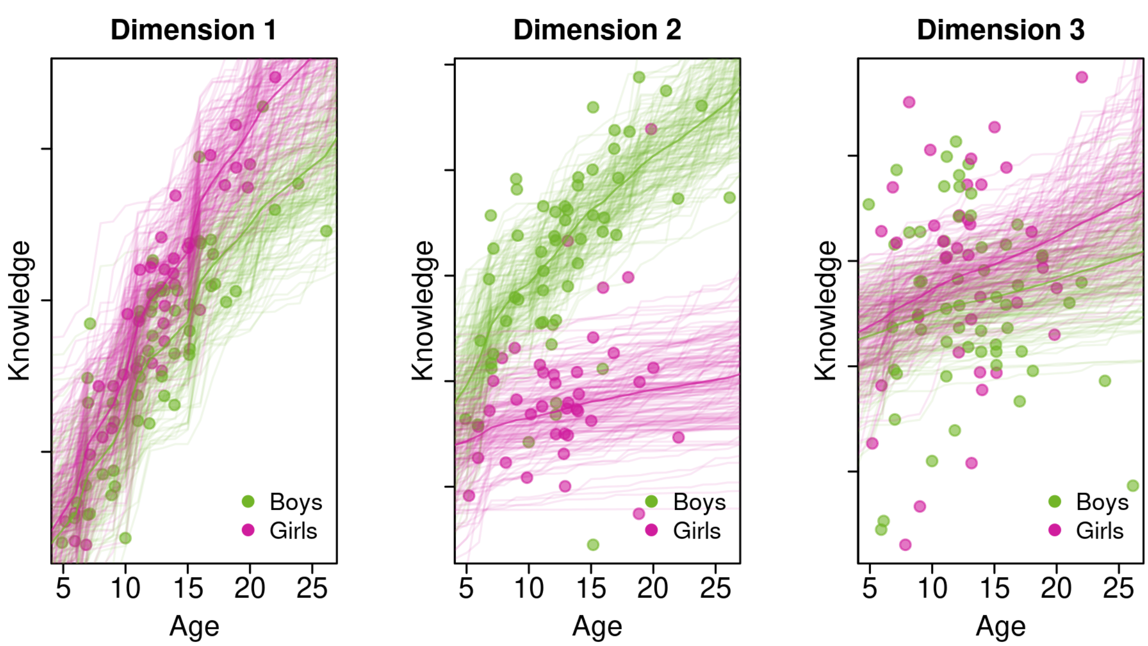

Figure 5: Individual knowledge K_i and predicted values by age and sex in three dimensions.

the causal influence of unmeasured household variables, so these estimates cannot be interpreted causally, as is the norm with control variables (Westreich & Greenland, 2013).

The first variable we considered is the activities practiced by children (defined combining reports by parents and the children themselves, see Supplementary section 9.3.2 for details), for which the effect on undifferentiated knowledge is substantial. Figure 6 plots how much advantage, in terms of time, an individual can gain (positive effect) or lose (negative effect) from practicing a specific activity. All else being equal, a person who hunts birds can reach the same knowledge of a non-hunting 20 year old up to 10 years earlier. Similarly positive effects are given by collecting shellfish, fishing and by tending to the family's livestock. On the contrary, working in the fields can hinder knowledge acquisition by more than a decade, as can attending to household chores. Activities practiced account for majority of the measured difference between boys and girls, so that, once their effect is controlled for, the difference in knowledge between sexes seems to disappear (see figure S16). Some portion of the measured association between activities and knowledge is plausibly causal, but note that there may be unmeasured common causes of both activity and knowledge, as well as some reverse causation, if knowledge is a necessary precondition for some activities. Therefore we suspect these activity effects are upper bound estimates.

We present the results of household family structure and school attendance in the Supplement 9.9. Co-residence of parents (figure S18) appears to have an effect on individual's knowledge. Mothers seem to boost their children's knowledge, helping to reach earlier, on average, the same knowledge of a 20 years old with no parents. The presence of fathers, on the contrary, has different effect on his sons and daughters, improving the knowledge of the former, but impeding learning about the environment for the latter. Schooling seems to at least partially slow down learning for girls, but has no effect on boys (figure S20). Birth order has no appreciable effect on knowledge (see figure S19 and Supplementary section 9.9 for more information).

3 Discussion

The observation that people in this sample learn during the whole pre-reproductive period complements previous work showing increases in knowledge during adolescence and adulthood (e.g. Koster et al., 2016; Schniter et al., 2021). Additionally, we show that the rate of acquisition is not constant, and that there are age 'hot-spots' for learning. Knowledge acquisition appears in our data to be fastest during middle childhood, between 7 and 12 years, after which its speed decreases. More novel is our use of causal modelling to explore the role of activities in shaping sex differences in ecological knowledge. We find that higher ecological knowledge is associated with activities like foraging, hunting and fishing, consistent with the general view that practice is important to the acquisition of ecological information, and more distally that early life history is shaped by the need to learn.

Most hypotheses describing the importance of knowledge for life history evolution propose that childhood emerges in the *Homo* lineage as a time to complete full growth of the brain during early childhood, after which the brain has to be filled with information during middle childhood (Thompson & Nelson, 2011). Our results are congruent with this view: after the brain reaches its full size, knowledge acquisition speeds up, maintaining a fast rate during the middle childhood years. Perhaps not incidentally, this period is marked by a slow down in somatic growth, which reduces the energetic requirements of children while they start to engage in productive activities and acquire the required knowledge. Adult provisioning and protection are needed up to at least the beginning of adolescence, but the first attempts at performing most activities happen well before 12 years, and allow children to have a buffer zone in their life history in which to try out various tasks with the back-up offered by parents and other caretakers (Lew-Levy & Boyette, 2018). During adolescence, learning is slower, although it keeps going until after sexual maturity, potentially providing opportunities for specialization.

Differences in knowledge between the sexes appear by age 7 and become more prominent during adolescence. Although Pemban children of both sexes live in close contact with the natural and cultivated landscape, boys begin to participate in more gender-specific activities in the forest and sea, such as hunting and fishing (see Lew-Levy, Boyette, Crittenden, Hewlett, and Lamb (2020) for

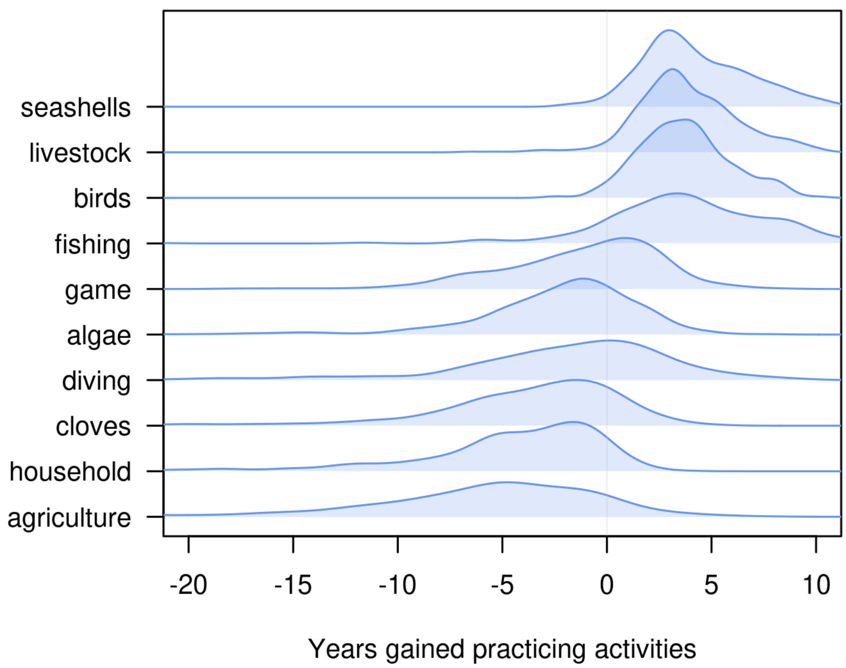

Figure 6: The plot describes how much advantage, in terms of time, an individual can gain from practicing an activity with respect to undifferentiated knowledge. The x axis represents the years gained, i.e. how much earlier (positive values) or later (negative ones) an individual practicing each activity would reach the same knowledge of a 20 years old individual not practicing that activity, all else kept constant. Activities such as shellfish collection and bird hunting could give up to ten years advantage in terms of knowledge to practicing individuals - although most people would gain two to five years. On the contrary, doing agricultural work (bottom row) seems to slow down learning. Notice that the tail of the distributions for the bottom 5 activities extends outside of the limit of the plot, with the 5th or smaller percentile below -20.

further examples of cross-cultural variation in gender segregation during play). Shellfish collection is the main activity in the wild practiced preferentially by girls, but young boys often follow their sisters in these expeditions, and are therefore exposed to this kind of knowledge. Accordingly, the two sexes will typically differ to some extent in the amount of exposure to information about the environment, with boys having access to more girl-specific knowledge than the contrary. Indeed, while both sexes learn at the same rate knowledge that is shared, see dimension 1 in figure 5, boys have access to a whole area of information that is precluded to girls, which is represented in dimension 2 in the same figure. Our result could help explain why previous studies showed inconsistencies in the amount of knowledge differences found between the sexes (Blacutt-Rivero et al., 2016; Cruz-garcia et al., 2018; Gallois et al., 2017; Geng et al., 2016; Schniter et al., 2021; Setalaphruk & Price, 2007). Indeed, the multidimensional nature of knowledge means that the survey design impacts the ability to measure knowledge evenly across dimensions, potentially overestimating the importance of one dimension above the others (e.g., a survey focusing on wild birds will show that males have much higher environmental knowledge, see Supplementary section 9.4.4 for observations on how the types of data we collected vary in reflecting knowledge differences between sexes).

The importance of activities in promoting the differences between the sexes is supported by the causal analysis of their effect. Once we control for activities, we can see that the differences almost completely disappear (see figure S16). Hunting, fishing and shellfish collection all have positive effect on knowledge, and they are practiced at different rates by boys and girls, so that knowledge differences between the sexes emerge through differential participation, rather than because of any presumed innate attitudes to environmental knowledge.

The differential participation in activities that involve the natural environment can also explain why residing with mothers appears to have a positive effect on knowledge for both girls and boys, but only the latter benefit from the presence of fathers. At least, this would be the case if both sons and daughters learn from their mothers when collecting shellfish on the reef, but only sons learn to fish with their fathers. Or if, as found by Hassan, Schaffnit, Sear, Urassa, and Lawson (2019), mothers don't discriminate, while fathers invest more in their male offspring. The fact that this is the only clear finding from our analysis of the effects of household composition on environmental knowledge may reflect the fact that children are immersed in a large and diverse social environment, which makes it difficult to investigate its effect on knowledge. As in so many contexts (Boyette & Hewlett, 2017; Lew-Levy et al., 2019, 2017), children are almost always surrounded by other adults, by older siblings or cousins, and by a varied set of peers and neighbours in play groups. Knowledge transmission is likely to happen through all of these ties, likely weakening any direct influences of household structure, particularly if children with few siblings are more likely to seek out neighbours and more distant relatives as playmates. Future investigations into the effects of the social environment on knowledge should probe friendship networks and household composition at a higher resolution.

Our analysis of the effects of participation in formal education on ecological knowledge does not yield a clear answer on whether formal schooling impacts ecological knowledge, consistent with previous work (Quinlan et al., 2016; Reyes-García et al., 2010). It is possible that the specific settings of the village where the data were collected (both forest and seashore are close-by) allow children to acquire enough experience of the natural environment irrespective of the amount of time they spend in formal education. But also, schooling might affect what children know about the environment, rather than only how much they know. It is even possible that information on other biomes learned at school substitutes for or even enhances locally relevant environmental knowledge. As such, no effect of schooling would be detected, as might be substituted by information on other biomes learned at school and result in no variation in total knowledge, as in our sample.

In summary, our results support the idea that the pre-reproductive phase serves as a period for knowledge acquisition. First, we demonstrate that, among children and teenagers in Pemba, knowledge increases with age in a non linear fashion and that middle childhood is a hot-spot for learning. Second, we show how knowledge differences among sexes can be ascribed to different dimensions of knowledge, which reflect specialization. These differences are not innate, but seem to be a product of labor division, given the role played by activities in driving differentiation of knowledge. Third, we show the importance of practicing activities for knowledge acquisition and, fourth, we find some evidence that the social environment influences knowledge of children, but more specific analyses are needed in this sense. All these results have significant implications for the hypotheses on the evolution of human early life history. Knowledge cannot be acquired very early nor in a short time because of the crucial role that activities play, exposing individuals to relevant information. There are physical constraints to achieve adult rates of success in most foraging activities (Bliege Bird & Bird, 2002; Bock, 2002), but children start trying them out much before they actually are physically apt and proficient (Lew-Levy et al., 2021), and during this time they seem to be acquiring the necessary knowledge (Lew-Levy & Boyette, 2018). Faster learning, boosted for example by innate behaviors acquired through natural selection, is probably not adaptive in humans because of the high behavioral flexibility we exhibit. Children have to learn in many different dimensions to complete different tasks, with differences between sexes and individual specialization.

These insights on the evolution of childhood could be strengthened by applying comparable methods to samples from other populations, thereby providing a more nuanced understanding of the relationship between age and knowledge (Deffner, Rohrer, & McElreath, 2021). With such data we can account for cultural variation, while at the same time produce comparable, non site-specific data to make adequate inferences on generalizable human learning patterns. For example, it might be interesting to examine whether the hot-spot age range identified in Pemba is a human universal, consistent with the brain-filling hypothesis, or variable across sites, more consistent with the idea that learning schedules vary according to the ecological affordances offered by different environments and cultures.

Moreover, we advocate for the realization of longitudinal studies, tracking the variation of knowledge over time in the same child. This would allow us to draw individual learning curves, and thus estimate general trajectories of knowledge acquisition. Longitudinal studies would also allow us to better understand the direction of causation between participation in activities and knowledge about these activities, as well as the effect of social environments.

Finally, we believe that understanding how and when ecological knowledge is acquired is an important goal in today's changing world. Local environmental knowledge is important to cope with climate change (Berkes & Jolly, 2002), and can boost the perceived value of plant foods, often considered weeds, which provide important ecosystem services (Turner et al., 2011). In fact we know that agricultural societies rely on the natural (uncultivated) environment for multiple services: archaeological evidence proves that the transition to agriculture did not exclude foraged food from neolithic diets (Ottoni et al., 2021), modern populations fall back on wild foods in case of famine (Walsh, 1995) and children are observed foraging in many different social settings (Lee & Brewis, 2009). Hence we believe that our study on ecological knowledge of children in Pemba can add a relevant contribution to the literature on how societies can adapt to social and environmental transitions.

4 Acknowledgments

This work would not have been possible without the kindness and hospitality of people in Pemba. In particular, the staff at the DFNRNR in Wete, Asha Yusuf Khamis and her family, our neighbors and the rest of the people in the village. To Dr. Martin Walsh, Massoud Bakar Massoud, Bakar Makame Khamis and Haji Masoud Hamadi a special thanks for helping reviewing the list of items of the freelist.

5 Author Contributions

IP, MBM and RM designed the study. IP collected the data. IP and RM performed statistical analysis. IP drafted the MS with inputs from RM and MBM.

6 Financial Support

This research is funded by the Department of Human Behavior, Ecology and Culture at the Max Planck Institute for Evolutionary Anthropology.

7 Conflicts of Interest declarations in manuscripts

The authors declare they have no conflict of interest.

8 Research Transparency and Reproducibility

The data that support the findings of this study are openly available in https://github.com/lalla-ilaria/Children_eco_knowledge.

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9 Supplementary

9.1 A word on Knowledge

Knowledge is interpreted here as a latent trait of individuals which underlies the probability of answering the questions in the sample correctly. Henceforth, statements such 'knowledge is influenced by' can be read as 'the probability of correctly answering the questions in the sample is influenced by'. Despite this practical approach, we did our best to improve the construct validity of our study, by both developing the questionnaire and managing the resulting data in collaboration with informants sharing language and culture with the interviewees. We then expect knowledge, as measured by our model, to reflect the general ecological knowledge possessed by individuals, but do not deal with general epistemological considerations on the connection between the two.

9.2 Sampling bias

As most observational studies, ours is a potential victim of sampling bias. The use of selection diagrams can help deal with sampling biases that do not interest the outcome variable. For example, controlling for the variables on which selection is happening can help balance samples (Deffner et al., 2021). Unfortunately, as a result of our opportunistic sampling strategy, our study is at risk of having sampled individuals because of their knowledge (if, for example more knowledgeable individuals were more likely to participate to the interviews). If this is the case, selection would have happened on the outcome node (see DAG in figure 3) and no statistical procedure can correct the resulting bias. But, luckily, we can estimate the presence of a sampling bias.

As a result of the opportunistic sampling, the sample contains almost all individuals between 5 and 20 years old living close to the research station where the researchers resided. This constitutes a - almost - complete sample for the sub-village where the research station is located. Individuals residing farther from the research station had lower rate of participation in the study, and hence we would expect selection bias to cause a difference in knowledge between individuals residing close and further from the research station.

To test for selection bias, we first added distance (of households from the research station) as a linear predictor of knowledge (the analysis was conducted on the 84 individuals for whom the GPS coordinate for household were available). The coefficient for distance was estimated to be at least partially positive, indicating some effect of a selection bias. In comprehensible terms, an individual living 450m away from the research station would reach the same knowledge of a 20 years old individual living 50m from the station 3.2 years earlier, on average. It is indeed possible that our sample includes more knowledgeable individuals than expected by chance.

We then run our main analysis describing the variation in knowledge by age and sex (model 1 in the main text) including only the 39 individuals residing in the sub-village, for which we have an almost complete sample. The results are shown in Figure S1 and are qualitatively comparable to the results for the entire sample.

To conclude, although we cannot exclude that our sample was biased - in fact we estimate that at least part of it was biased in a non-recoverable way - we argue that the qualitative results presented in the paper hold despite this problem, as the unbiased results are comparable.

9.3 Demographic interviews. Notes on age and activity variables.

9.3.1 Notes on reported and other ages

The present analysis focuses on age of children in a population where individuals do not celebrate birthdays and only few have or conserve birth certificates. A word on how age of individuals was set is hence needed. The age for each individual was assigned individually after cross validating four sources of information: ages reported by parents or guardians during the census interviews; ages reported by the children themselves during the knowledge interviews; when available, ages reported in the registry of the local elementary school, where most of the individuals in the sample were, at some point, enrolled; focus interview with Amina Mussa Hamadi, mother of some of the interviewees

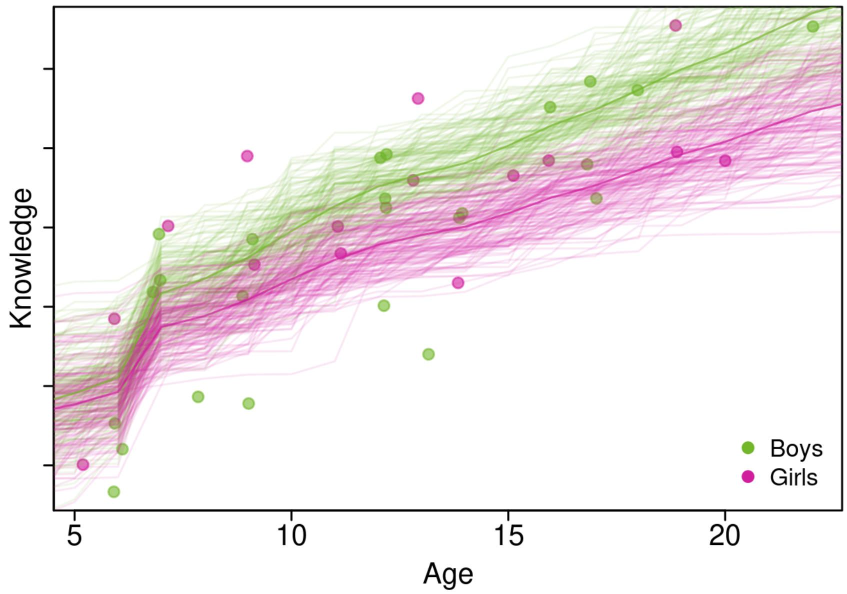

Figure S1: Knowledge estimated at different ages for the subset of individuals living close to the research station. In this sub-village, almost all individuals between 5 and 20 years old have been sampled, making this sample most likely exempt from sampling bias.

for whom a birth certificate is available, to establish relative age of other children (e.g. child A is 8-10 months older than child B). The most supported age has then been assigned manually. With this process, we believe to have substantially reduced error around individual ages, but any year specific effect is still to be distributed over similar ages (e.g. in figure S7, higher effect of ages 7 and 11 is probably spread over the whole period 6-12).

9.3.2 Activities details

As complementary information of both the census and knowledge interviews, parents and children were asked whether each child in the sample practiced one of 10 different activities. Here follows an ethnographic description of what each activity entails.

- **Seashell collection:** The coastline close to the village is a very good place to collect seashells. This activity is practiced by girls and women of all ages, although adults participate less frequently, and by young boys, who follow their mothers or older sisters. It mainly involves spotting the position of shells under the sand and extracting them bare-handed or with the help of a knife. Different species of crabs are also pursued, as well as other occasional preys. This activity is temporally limited by the height of the tides, as most of the sand bottom remains covered and inaccessible during high tide. The least exploited areas, that emerge from the water only when the tide is particularly low, are the most productive for foragers, so that when a tidal minimum happens on a weekend, people arrive from other villages to collect seashells close to the village, but normally only few people can be seen walking along the coast at low tide.

- **Fishing:** Most adult men in the village practice some sort of fishing at least occasionally. Boys start to accompany their fathers and uncles sometimes as early as 12 or 14, but often don't start participating until they reach 16 or 18. Different types of fishing are practiced in the area, from diving alone with a mask in shallow water to capture small fish named *ngogo*, to participating in larger fishing parties together with men from other villages on motor boats. But most boys and young men in our sample practice small scale fishing, from dugout canoes and small boats.

- **Livestock handling:** Boys and young man are sometimes responsible for the family livestock. This mostly entails moving a couple of tethered cows or a few goats from one patch of grass to the next few times a day, and bringing them to the river to drink.

- **Bird hunting:** This activity is practiced by many young and older boys with a variety of techniques. These include roaming the *shambas*, the cultivated fields around the village, with a slingshot trying to bring down little birds; using glue extracted from a local vine to which birds get stuck, once sticky sticks are placed on frequently visited branches; and also placing snares in the forest to capture terrestrial birds such as ibises.

- **Hunting with dogs:** Older boys and young men sometimes leave the village in noisy hunting parties accompanied by a variable number of dogs. These trips are usually aiming to kill monkeys or civets that attack the village chicken, and in general animals that are considered a pest.

- **Diving:** Some individuals practice some form of spearfishing, with or without oxygen tanks. These are usually older boys and young men, who bring fishing to an advanced stage.

- **Algae farming:** Many women and girls farm algae destined to the Asian food market. This is a very tiring activity, but one of the few commercial activities that women practice with some frequency. It does not require much knowledge, but spreading, collecting and drying the algae takes a lot of time.

- **Cloves picking:** During harvest season, most young boys and girls are hired by the families owning clove trees to pick the little buds these plants produce. This activity is limited to younger, lighter individuals who do not break the fragile branches of the trees, and is quite dangerous. But it is one of the main sources of cash for many families and most children engage with it for many years.

- **Household chores:** With this expression we include all sort of household relate tasks, such as washing clothes or pots and pans at the stream, or cooking. These tasks are mostly practiced by girls, although some boys contribute with some smaller tasks, such as bringing water from the well.

- **Agriculture:** Farming seems to be the main occupation of most families: tilling the rice field, planting stalks of cassava, weeding and harvesting peanuts are rotating as main activities depending on the season. In these families, most people of all ages contribute to agricultural tasks, as farming is not automatized and hence it is very labor intensive.

9.4 Freelist, questionnaire and image recognition. Collection and differences in results.

All interviews were conducted by IP in the village of Bandarikuu, Pemba. Children who volunteered for the interviews either showed up by themselves at the research station (hence the almost complete sampling of children living in the neighboring houses) or were encouraged to participate by friends and siblings (who received no remuneration for this). Participating children received a pen/pencil and a candy after the end of the interview, but such small gifts were handed out by the researchers regularly to all children, so participation did not guarantee any special treatment. Interviews were carried out in a (relatively) protected location to reduce probability of interviewees being influenced by other participants' answers. Audio recordings of (almost) all interviews are also available.

	All ages	Aged <10	Aged 10-20	Aged >20
n	94	27	64	8
Max n items listed	342	300	342	275
Min n items listed	7	7	18	59
Mean n items listed	132.8	110.5	133,1	196.1
SD n items listed	78.0	86.5	69.3	74.2

Table S1: Total number of items listed in freelist for the whole sample and by age group (including repetitions and non coherent items).

9.4.1 Freelist, details

Interviewees were asked to freely list all living creatures they knew with the question 'Could you tell me all the living creatures you know which live in the fields and village/forest/sea. All the animals, birds, fish, critters, trees and plants you can think of (Swahili: *"Unaweza kuniambia viumbe vyote vinaoishi shambani na kijijini / msituni / pwani na baharini. Wanyama wote, na ndege, samaki, wadudu, miti na mimea wewe unaweza kukumbuka'*). The question was repeated at least three times -once referring to fields and village, once to forest and once to the sea- to ensure that interviewees would mentally explore all environment types. The same question was also repeated if the interviewee seemed confused or paused for a very long period of time. Listing all types of creatures (animals, birds etc) also aimed at encouraging the interviewee to search among all living creatures. The words listed are culturally relevant for categorizing animals and plants: *wanyama* refers to land mammals and other ground animals, *ndege* are all birds and bats, *samaki* includes fishes and other marine animals such as whales and dolphins, *wadudu* is a word for pests, and includes most insects, but also often other animals percieved as pests such as rats and snakes, *miti* and *mimea* are respectively trees and shrubs. The freelilst section of the interviews was terminated when the interviewee stated he/she couldn't remember any more creatures or if the interviewee did not add any new item even after being primed multiple times by repeating the question.

The possible presence of a ceiling effect -i.e. if interviewees would reach a maximum number of items listed because of other reasons than knowledge - was a concern when designing and carrying on the interviews. A ceiling effect would be problematic especially if it correlates with age, e.g. younger individuals could get bored earlier and stop listing creatures even if they actually know more of them. We do not believe this to be the case, as the total number of items listed by individuals does not seem to differ among age groups (see Table S1). The maximum number if items listed is around 300 in all age groups, the highest number of items has been listed by a 12 years old individual. In general, most individuals kept listing items even when they had exhausted all their knowledge on the natural environment, by repeating items already listed or by listing objects and other non living things.

To deal with the repetitions and non coherent answers, and more generally to make sure the dataset was correctly representing knowledge of individuals, each item listed has been assigned to one of the following categories *wanyama* (W), *ndege* (N), *samaki* (S), *wadudu* (D), *miti/mimea* (M). Lists of items can be found in the GitHub repository, including those considered 'not_a_creature' and hence removed from the dataset. The list has been additionally reviewed by three separate local specialists (Massoud Bakar Massoud - Head of Planning and Administration at DFNRNR Pemba, Bakar Makame Khamsis - field assistant, and Haji Masoud Hamad - DFNRNR) and as well as by Dr. Martin Walsh (Adjunct Professor in the School of Business Studies and Humanities, Nelson Mandela African Institution of Science and Technology (NM-AIST)), expert of Swahili culture and ecological lexicon.

After cleaning, the list comprises 708 items, of which 231 named by a single individual. The item named by most individual is the mango (tree and fruit associated), named by 82 individuals.

9.4.2 Questionnaire, details

The 50 questions in the questionnaire have been developed in collaboration with the personnel of the DFNRNR in Pemba and through focus groups involving several adults in the village of Bandarikuu. The full list of questions, in English translations, is available in table S2, while the original Swahili can be found in the GitHub repository.

QN number	English translation	Right answer	Question type
1	Do bats make eggs(A) or give birth(B)?	B	forest
2	Do hyraxes stay on the floor only(A) or climb trees as well(B)?	B	forest
3	Helmet shells(A) or mud whelks(B) live in between the mangroves?	B	shell
4	Can catfishes swim in the sea(A) or only in the river(B)?	B	forest
5	Do vultures eat meat(A) or fruits(B)?	A	forest
6	Mbaazi(A) or beans(B) is a vine?	B	farming
7	Do kingfishers eat insects(A) or fish(B)?	A	forest
8	When scared, the squid releases ink. True(A) or false(B).	A	fishing
9	Per single event, do sharks give birth to about five(A) or fifty(B) offspring?	A	forest
10	Green spotted snakes are dangerous. True (A) or false(B).	B	forest
11	Which season is good for cultivating seaweed, long dry season(A) or long rainy season(B)?	A	farming
12	Do sea turtles return to their beach every six months(A) or one-two years(B)?	B	fishing
13	Who eats snails, the civet(A) or the mongoose(B)?	B	fishing
14	Civets eat the meat of oil nuts. True(A) or false(B).	A	forest
15	Bushbabies sleep at night(A) or during the day(B)?	B	forest
16	Mkuu wa usiko is used as a medicine for the head(A) or the stomach(B)?	B	medicine
17	The territorial vervet monkey male lives with his grandchildren(A) or by himself(B)?	B	forest
18	Cone shells have venom. True(A) or false(B).	A	shell
19	Bushbabies, when eating bananas, eat one at a time(A) or they ruin the whole batch(B)?	A	farming
20	Which bat uses its ears to fly, flying fox(A) or banana bat(B)?	B	forest
21	Bats produce excrements out of their mouth. True(A) or false(B)?	B	forest
22	Groupers have many(A) or no(B) teeth?	A	fishing
23	Which banana is good for cooking, mkono wa tembo(A) or kukusa(B)?	A	farming
24	Rays sleep between the corals(A) or in the muddy patches(B)?	B	fishing

QN number	English translation	Right answer	Question type
25	Whales travel to Pemba to give birth(A) or to rest(B)?	A	fishing
26	The mgulele tree makes fruits that resemble java plums(A) or custard apples(B)?	A	farming
27	Chaza(A) or tondoo(B) is hard to kubanja?	B	shell
28	Hyraxes have no fingers(A) or have three fingers(B)?	B	forest
29	The mti ya ulaya tree grows in the forest border(A) or in its center(B)?	A	forest
30	Which plant is a good medicine to kill fly larvae, msindu(A) or forest tonga(B)?	B	medicine
31	Shrimps can swim in the sea. True(A) or false(B).	A	shell
32	Which wood is good to build boats, mgulele(A) or mkarati(B)?	B	building
33	Geckos can be which color, white(A) or green(B)?	B	forest
34	Tunas reach the size of a cow(A) or of a child(B)?	A	fishing
35	After planting sweet potatoes, two(A) or four months(B) are needed before harvesting?	B	farming
36	The octopus is fished with fishing spears(A) or with nets(B)?	A	fishing
37	Kichachuli is the offspring of the vervet monkey(A) or of the civet(B)?	A	forest
38	Sea turtles travel in the cold(A) or hot season(B)?	A	fishing
39	Which shark is dangerous, nyambrani(A) or charawanzi(B)?	B	fishing
40	When the tide is low, can you find cowrie shells or razor shelld on the beach?	B	shell
41	Swifts travel to Europe. True(A) or false(B)?	A	forest
42	Ducks lay eggs in the short(A) or long(B) rainy season?	B	forest
43	Which fruit is produced once a year, mkorosho(A) or java plums(B)?	A	farming
44	The offspring of dolphins drink milk. True(A) or false(B).	A	fishing
45	Which coconut lives a longer life, the cultivation one(A) or the normal one(B)?	B	farming
46	The caterpillar is the offsping of the butterfly. True(A) or not true(B).	A	forest
47	Lion fishes are dangerous. True(A) or false(B).	A	fishing
48	Frogfishes swim(A) or walk on the bottom of the sea(B)?	B	fishing

QN number	English translation	Right answer	Question type
49	Of the plant mjafari, the roots(A) or the leaves(B) are used as medicine?	A	medicine
50	Which period is good for panga: beginning(A) or mid(B) moon?	A	shell

Table S2: The English translation of the 50 questions asked in the questionnaire section of the interviews, together with correct answer and type of question.

Figure S2: First image shown to interviewees during the image recognition task. It contains three creatures to recognize: a snake, an ant on the branch and the plant itself.

9.4.3 Image recognition, details

The image recognition task was the last task of each interview. The interviewees were shown 27 pictures on a 9.7" screen, always in the same sequence, as we were interested in variation among individuals, more than in characteristics of the picture themselves. Each picture shows from 1 to 7 species of plants and animals. The interviewees were asked to point at and name all the living creatures in the picture. For example, in Figure S2, there are three organisms that interviewees can name: a snake, an ant on the branch and the plant itself. Any answer was recorded and, in a second stage, all the answer have been reviewed in collaboration with adult volunteers in the village. All possible answers were divided in acceptable (even if not strictly correct) vs. non acceptable. For example, the word *nyoka*, meaning 'snake', was not considered acceptable for the snake in the picture, as it is too generic. Instead, *gangawia* was considered an acceptable alternative to the correct *ukukwi* as the two species are similar. One plant was excluded from the analysis as no interviewee was able to recognize it.

9.4.4 Notes on methods. Comparisons of results from different question types.

The three types of data collected during the interviews have been combined in the main analysis to yield a total estimated knowledge measure for each individual. Here, we present the separate results from the three types of data and discuss the pro and cons of each in terms of methodology.

The freelist represent the majority of the data points. As each of the 708 items was treated as a question that could have been answered correctly - i.e. that item was named - by each individuals, freelist items alone represent 85.4% of all data for each individual. This means that freelist data provide the majority of information for the main model in the paper. The estimates from freelist data are shown in Figure S3 panel *a* for one and S4 for three dimensions. Panels *b* and *c* show knowledge estimated from the questionnaire and image recognition data only, respectively. As expected, they contain approximately the same information as the full model, to which each contributes: knowledge increases with age and there are differences between the sexes. Both the questionnaire and the image recognition, though, estimate much higher knowledge for boys than girls. This could be due to a

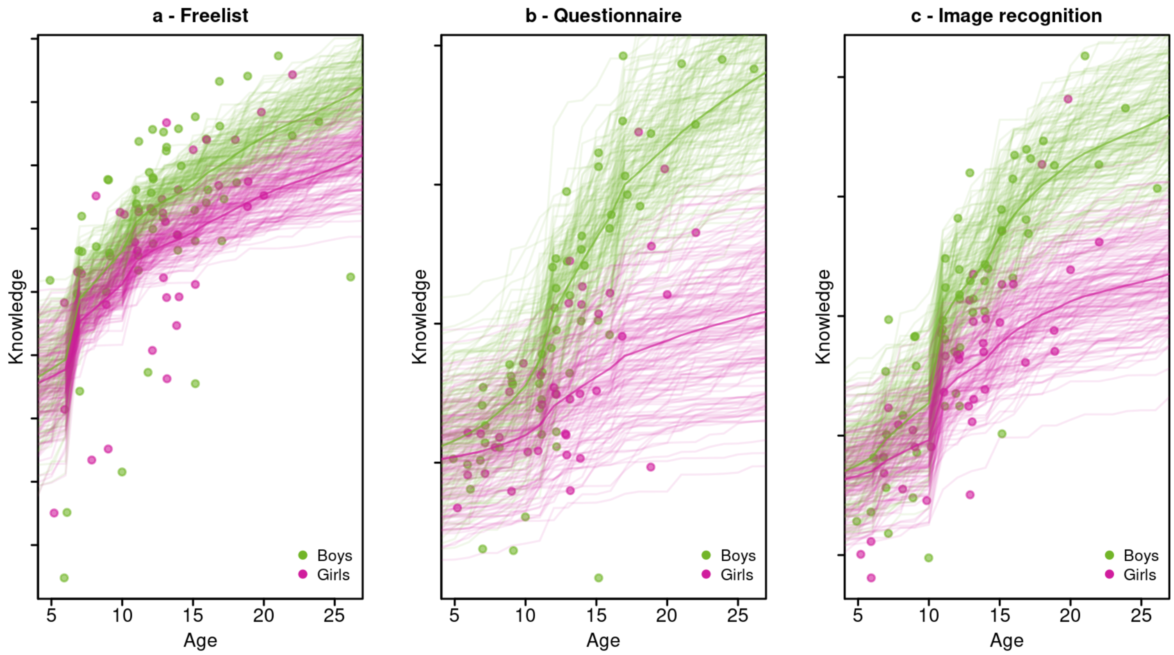

Figure S3: Individual knowledge and predictions per age and sex groups estimated from single types of data: panel *a* is estimated from freelist data, panel *b* from the answers to the questionnaire only and panel *c* from the image recognition task.

bias in the way the questionnaire and image recognition were constructed, given that, compared to the freelist, the agency of the researcher was much more important in these two types of question. In general, knowledge of individuals as estimated with each of the three question types alone positively correlates (see figure S5, suggesting that they describe overall the same individual characteristic. Moreover, if looking at the dimension analysis, we can find the three dimensions of knowledge described in the main text also in the freelist data (Figure S4) and in the questionnaire and image recognition, although for these two types of questions the number of data points is not sufficient to estimate clear age and sex specific trajectories.

IRT models allow to evaluate difficulty and discrimination for each item (creature named, question in questionnaire and creature in images). We can hence compare how effective are the types of question in helping us estimate knowledge. We can see the curves describing difficulty and discrimination of items in freelist, questionnaire and image recognition in figure S6, left, middle and right panel respectively. The position of the center of each curve on the x axis represents the difficulty of a question, while the inclination represents the discrimination. We can see that the three types of question do a decent job of helping us estimate knowledge. Most questions are quite discriminatory and vary in difficulty so that each type of question alone could potentially be enough for estimating knowledge, at least in one dimension (note that these plots describe parameters from Model 1 described in the main text, not from the models applied to each type of question separately).

From these observations we can draw some general conclusions. First, all the data collected are a good description of knowledge of individuals. Different types of questions produce comparable results, so we expect to be observing some individual characteristics that we could describe knowledge. Second, despite this, the type of data are not interchangeable and the decisions of the researcher might affect knowledge estimation. We observe this looking at how the results from the freelist differ from those of the questionnaire and image recognition (in figure S3), which are more impacted by data collection strategies (devising questions, choosing images). Third, the freelist appears to be the most effective way of collecting data, as it allows to collect many more data points with

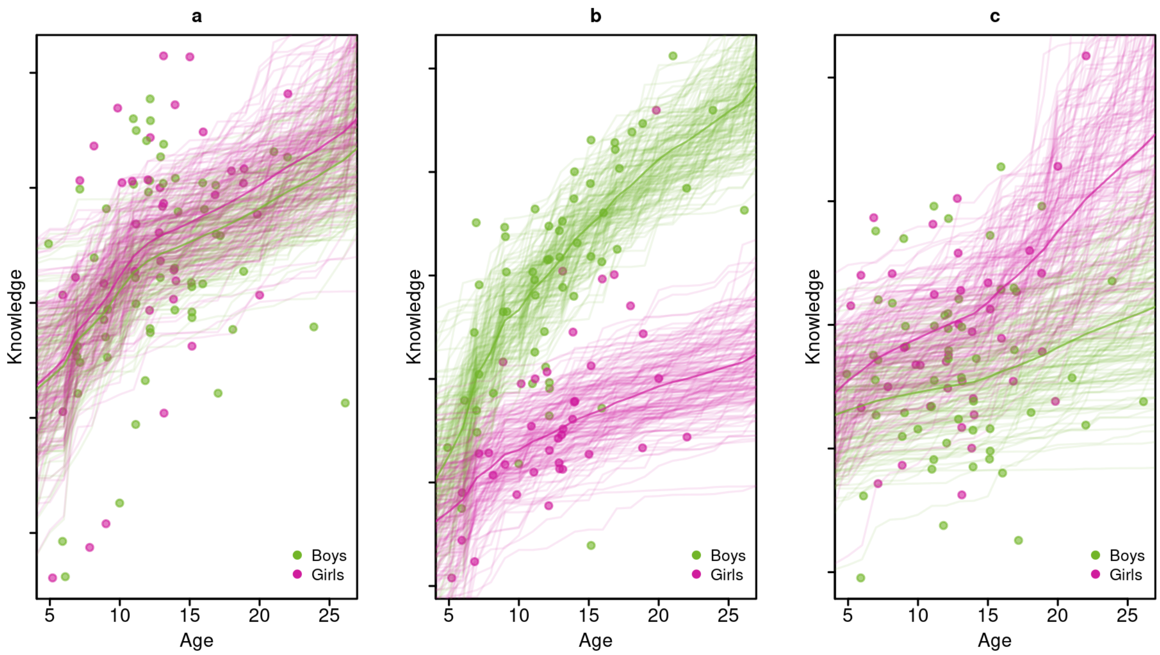

Figure S4: Three dimensions of knowledge as estimated from the freelist data only.

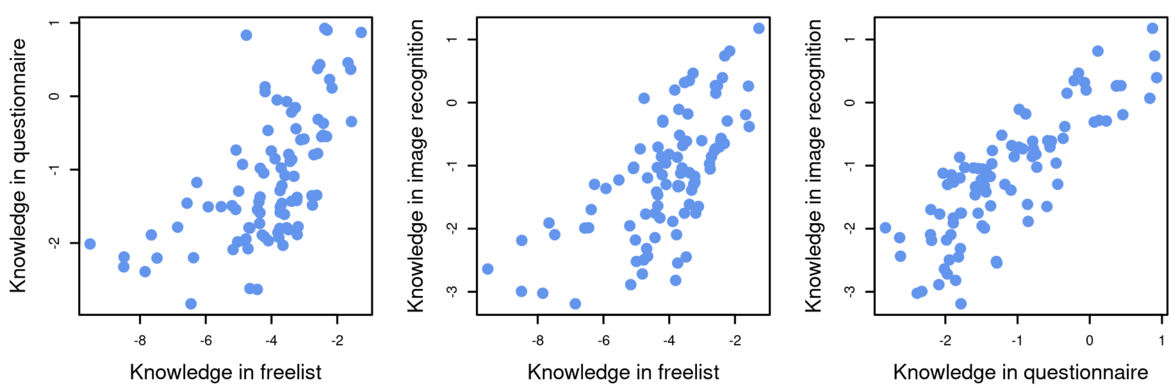

Figure S5: Knowledge estimated by each question type alone.

less effort (the design of questionnaire and the choice of images are very time consuming). Maybe more interestingly, freelists are less conditioned by the choices of the researcher, potentially yielding results that better describe reality. Post collection treatment of data has larger impact in the case of freelisting, but it is less likely to be gender biased.

9.5 DAG: Factors influencing Knowledge

Explicitly defined causal relationships described below are at the basis of both data collection and the choices guiding the analysis, including simulated data. Here follows a description of the factors we expect are exerting an influence on knowledge, with their causal implications:

Age Knowledge changes as individual get older. We expect to observe an increase with age, with individual differences that can emerge as a result of several factors. Age has a direct effect on knowledge, as it stands for increasing cognitive abilities of human brains that allow to store and manage information (Age → Knowledge). But also, and maybe more importantly, the total effect of Age include paths passing through the other factors: as individuals get older, other traits change, which have an effect on knowledge. As individuals age, the time they spend performing specific activities varies (Age → Activities), they start or stop going to school (Age → Schooling), or their family situation changes (e.g. new siblings are born, Age → Family).

Sex We do not expect a direct effect of sex of individuals on knowledge. Rather, we think of gender differences as influencing both the probability at which activities are performed, some tasks being typically done by girls and other by boys, as well as, potentially, school attendance (Sex → Activities and Sex → Schooling).

Activites In our expectations, the activities children perform more frequently have a strong influence on knowledge (Activities), both because of the exposure to the relevant information while performing the activity and of the increased returns derived from learning these information. When not in school, children in Bandarikuu spend their time doing domestic or farming chores, hunting, collecting seashells, fishing or playing, at different probabilities as they get older. Some of these activities, such as hunting, are expected to have a larger effect on the knowledge of the natural environment.

Family Family context, such as the presence of parents or older siblings, is thought to influence what and how much children know (Family → Knowledge). Engaging in activities with parents, can have an impact on the acquisition of knowledge related to those activities. Also, the simple presence of adults in the households can have a similar effect just by exposing children to conversations about subjects. Domestic situations can have large effect on the activities children perform (Family → Activities). Older same sex siblings can have positive effect on knowledge by representing a model and introducing individuals to specific activities (imagine an older brother teaching to shoot with a slingshot) or have negative effect if they fulfill a specific role in the household (only one person is sufficient to take care of the cattle of a single family). Younger siblings could change the expected time allocation into activities (for example reducing the time one can spend roaming the forest in exchange for time spent taking care of them). Family context and attitudes can also influences the effort children are allowed, or pushed, to put in formal education (Family → Schooling).

School The time and effort children invest in formal education can have different effects on knowledge of the natural environment. On the one hand, it can increase the the amount of information individual can manage. Ont the other hand, though, it can imply an opportunity cost by reducing the contact with natural environment (Schooling → Knowledge).

Summarizing, we expect knowledge to increase with age, to vary in accordance to which activities are performed, as certain activities favor the learning of ecological knowledge; by family, as access to knowledge depends on the access to older individuals able to transmit it, for example; and probably by access to schools, that provide certain types of knowledge but not others.

9.6 Model details

As mentioned in the main text, the models used are composed of two main parts: an IRT model that estimates knowledge from the answers to questions, and a generalized multilevel model that estimates the effect of various predictors on individual knowledge measures. Here we will describe more in detail the functioning and measures of the two parts.

The Item Response Model estimates a measure of knowledge for individuals in a latent scale (i.e. the absolute values have no meaning, what matters are the measures in relation to each other) in association to question parameters. It works by estimating an S shaped logistic curve for each question which describes the probability of answering the question correctly over the latent knowledge space (see figure S6). An individual's position on this axis is estimated according to which questions were answered correctly. Questions vary in difficulty b and discrimination a, which is a strength of IRT models in the fact that they do not assume all the questions to be equivalent. Difficulty is represented by the position of the curve for each question on the x-axis - harder questions are placed to the right while easier questions are on the left. The inclination of the curve indicates how discriminatory each question is, i.e. how much it can help distinguish knowledgeable people from not-so-knowledgeable ones. Most questions have quite good discrimination -their curve raises fast, drawing a sharp S- but some are not very good at discriminating. For example, a smooth S shape is very evident for a couple of items in the image recognition plot in the right panel (figure S6). In addition to difficulty and discrimination, questionnaire items have a third parameter: 'pseudo-guessing' c. These items represent a choice between two options, which means that individuals could have 50% probability of answering correctly just by answering randomly. But in practice individuals do not answer at random, and baseline chance of answering correctly varies from question to question. To deal with this problem, a 'pseudo-guessing' parameter estimates the probability of answering the question correctly by chance. The curves in the middle panel (figure S6), indeed, do not start from zero, but rather from the estimated c value, which means that even individuals with very low knowledge have a probability greater than zero of answering correctly.

$$
\begin{aligned}
Y_{i,j} &\sim \text{Bernoulli}(logit(p_{i,j})) \\
p_{i,j} &= c_j + \frac{1 - c_j}{1 + \exp^{-a_j(K_i - b_j)}}
\end{aligned}
$$

Knowledge of individuals is represented in figure S6 by the position on the x axis of the blue dots superimposed to the curves (the position at y = 0.5 is arbitrary). The model estimates it simultaneously to the question parameter, so that each observation (the answer of the ith individual to the jth question) contributes to all these parameters. Knowledge is the same in all three panels, as the three data types contribute to the estimation of a single measure of knowledge.

The values on the x axis are those of the latent dimension of knowledge, which is scale-free, so that they have no absolute meaning. In our model, most of the knowledge estimates are negative numbers, but this does not mean that individuals have negative knowledge. Rather, the whole latent space is pushed into the negative area of the plot by the fact that there are many freelist items with a high difficulty. These are all the items named only once, for which the model cannot estimate different difficulty - because they are all named once - but which clearly the majority of individuals could not name. These are visible crowding the area around 0 in panel (a).

Once knowledge is estimated in the IRT part of the models, the effect of individual and social characteristics are estimated in the second part. Each year contributes a proportion of the total age effect. Figure S7 shows the proportion of the total age effect relative to each year. The estimates are relative to the δ_y parameters, with $\delta_{y=1}$ having value of zero. The actual effect of age for an individual of age y is the proportion of β equal to the sum of all δ_y parameters for the younger ages. Because the sum of all δ_y values is equal to one, individuals with maximum age have the full effect of β. A detailed description of the statistical approach to ordered categorical variables used here can be found in Chapter 12.4 - pages 391 to 396 - of *Statistical Rethinking* (McElreath, 2020).

In addition to the models described in the main text, we present here the models estimating the effect of birth order and of school participation. In both cases, the effect of the factor is modeled as an ordered categorical, as in the case of age. Notice that schooling is modeled as the effect of not participating to school (each class not completed gives an increasing proportion of the total effect of not participating), but other ways of describing school attendance yielded the same results.

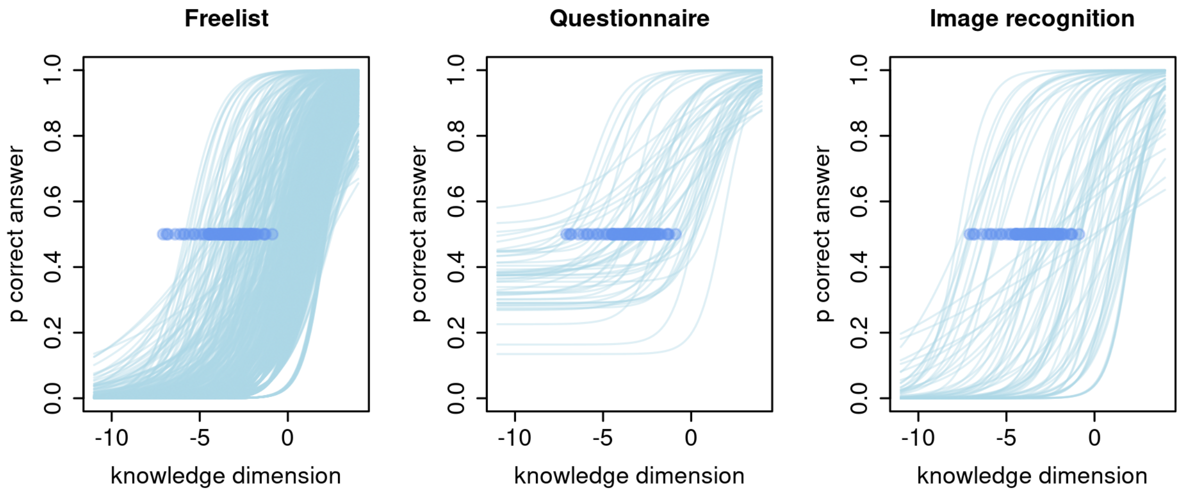

Figure S6: Logistic curves describing difficulty and discrimination of items in freelist, questionnaire and image recognition tasks respectively. Estimated knowledge of individuals has been superimposed as dots placed at the arbitrary y value of 0.5. The x axis describes the latent knowledge dimension.

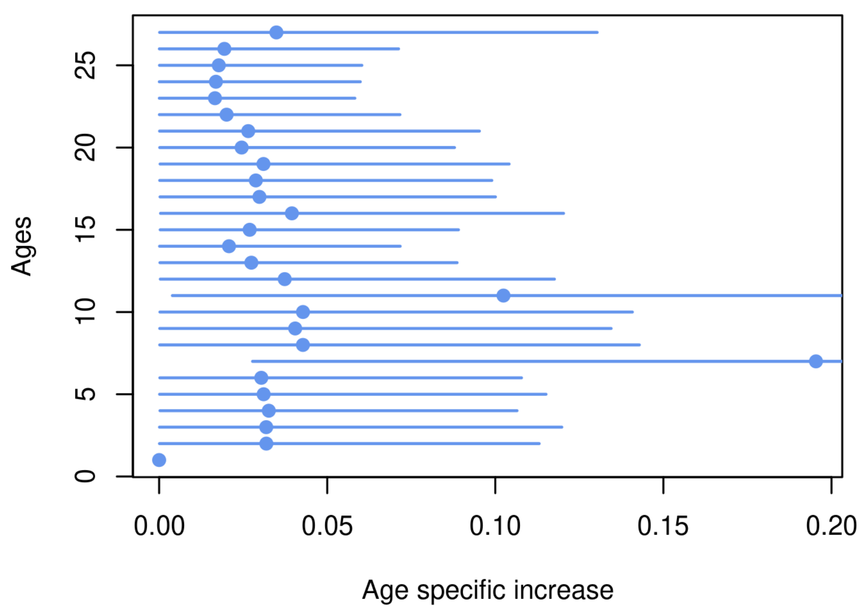

Figure S7: Proportion of the total effect of age relative to each year. These represent posterior estimates of δ_y parameters.

$$K_i = \alpha_i \sigma_\alpha + \eta_h \sigma_\eta + \beta_s \sum_{y=1}^{Age_i} \delta_y + \lambda \sum_{Sib=1}^{Sib_i} \delta_{Sib} \tag{1}$$

$$K_i = \alpha_i \sigma_\alpha + \eta_h \sigma_\eta + \beta_s \sum_{y=1}^{Age_i} \delta_y + \zeta_s \sum_{Sch=1}^{Sch_i} \delta_{Sch} \tag{2}$$

All models are coded including a different parameter per each dimension.

$$Y_{i,j} \sim \text{Bernoulli}(logit(p_{i,j})) \tag{3}$$

$$p_{i,j} = \sum_{d=1}^{d=D} p_{i,j,d} \tag{4}$$

Moreover, we need to mention that some adjustments were necessary to deal with the fact that all knowledge measures resulting from the IRT part of the model were in the negative space. In order to allow the function describing the categorical effect of age and the other parameters to move in this space, a global intercept ω was included in all models. This parameter moves the baseline of the functions below zero, to allow the other parameters to be positive. The prior for this parameter was negative (mean = -5), but very weak (sd = 3). The posterior values for ω are around -6 in Model 1 with one dimension, but vary in the models with more dimensions from -2.1 to -3.7. These measures have no biological meaning, but allow the other parameters to be comparable.

The full Model 1 used in the analysis looks like this:

$$\begin{aligned}
&Y_{i,j} \sim Bernoulli(logit(p_{i,j})) \\
&p_{i,j} = \sum_{d=1}^{d=D} p_{i,j,d} \\
&p_{i,j,d},_d = a_{j,d}(K_{i,d} - b_{j,d}) \\
&K_{i,d} = \alpha_{i,d}\sigma_{\alpha,d} + \eta_{h,d}\sigma_{\eta,d} + \beta_{s,d} \sum_{y=1}^{Age_i} \delta_{y,d}
\end{aligned}$$

9.6.1 Choice of priors

Priors for the parameters in the models were chosen in order to guarantee that the polarity of the latent axis would place people with more knowledge as having higher values than people with less knowledge. Simulated logistic curves describing difficulty and discrimination of question parameters with the priors chosen in for the models presented in the main text are shown in figure S8. These are

$$\begin{aligned}
a_j &\sim \text{Half-Normal}(0,1) \\
b_j &\sim \text{Normal}(0,2)
\end{aligned}$$

The same model has been run changing the priors for b to a Normal distribution with mean zero but standard deviation of 1 or 3. The resulting values of K and curves for question parameters can be seen in figure S9, where the curves and knowledge values in panel a are the product of Model 1 (equation 3) with prior $b \sim$ Normal (0,2), whereas panel b and c are respectively from the same model but with priors $b \sim$ Normal (0,1) and $b \sim$ Normal (0,3) respectively.

Finally, Figure S10 represents the priors for the curves that relate age and sex to knowledge. The priors are very vague and allow many possible relations in the space. In green and purple are shown the average values of the posteriors for these curves as estimated by Model 1.

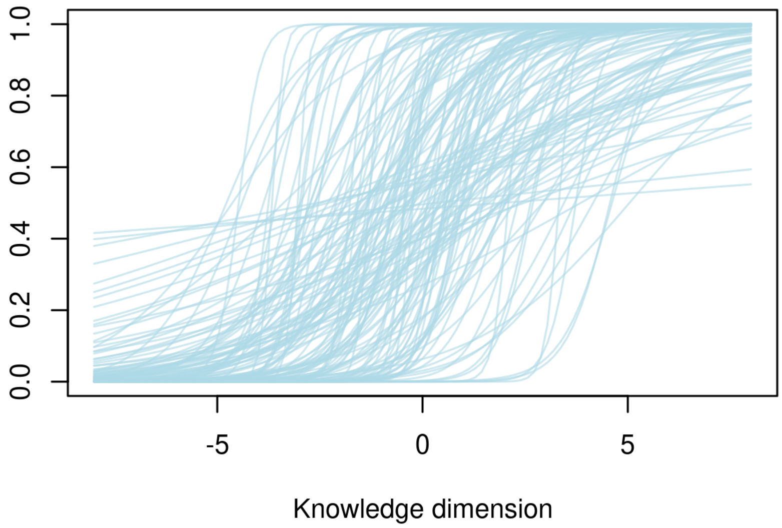

Figure S8: Simulated priors for question parameters in the IRT section of the model.

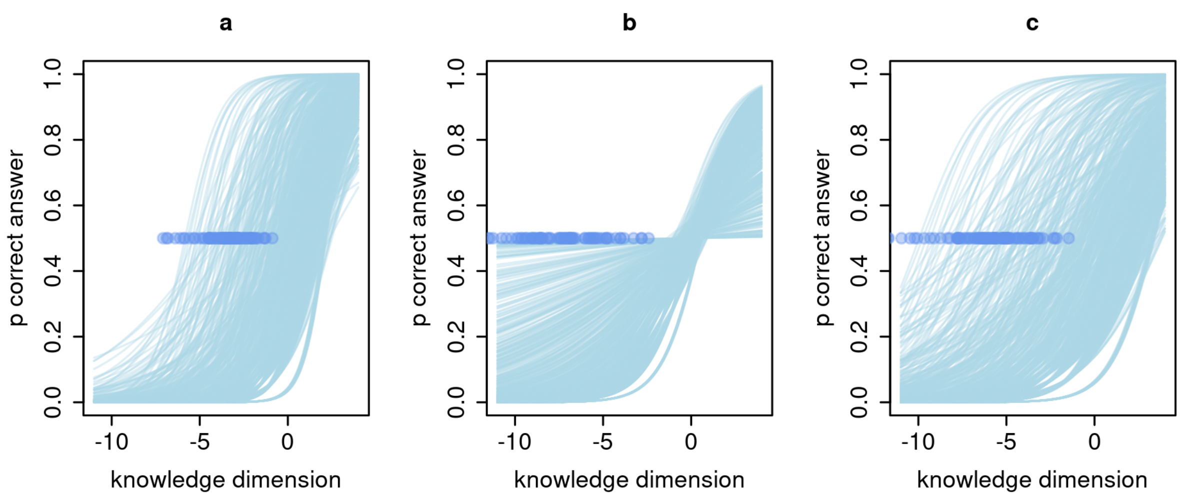

Figure S9: Knowledge of individuals and curves describing question parameters from the posterior distributions for three models fit with different priors for difficulty of questions. Panel a refers to the model fit with $b \sim$ Normal (0,2), which is the priors used in the models described in the main text. Panel b used $b \sim$ Normal (0,1) and panel c $b \sim$ Normal (0,3).

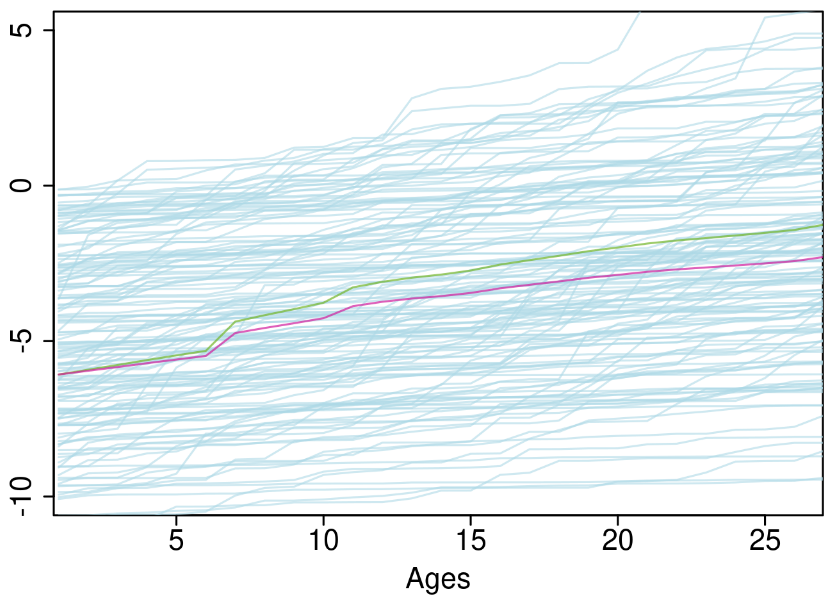

Figure S10: Simulated priors for individual parameters in the second section of the model. In green and purple are the averages of the posterior parameters depicted in figure 4, for comparison.

9.6.2 Label switching

One problem introduced by the use of a Multidimensional IRT model is label switching. This happens when parameters are not uniquely defined and two or more parameters can 'exchange values'. In the case of Multidimensional IRT models, this happens because there is no order in the dimensions and parameters can assume in each dimension any of the possible values for that parameters. So, running the model over multiple chains could mean that the chains could settle on different values: chain 1 assigns the value 2 to the first dimension and 4 to the second, while chain 2 does the contrary. Each chain samples fine and clearly distinguishes between the dimensions, but the final result, that averages between chains, will show no difference between the dimensions. Luckily this behavior is easily recognizable by simply visually inspecting the chains, and can be avoided by using a single chain. Some label switching can remain when running a highly dimensional model (traceplots show some switching in the model with 5 dimensions, for example), but up to three dimensions no label switching has been observed in our models. These have been run on longer chains to ensure comparable results to those of multiple chains.

9.7 Simulation

Preliminary to the data collection, we simulated data in silico to test the models and inform data collection procedure. The simulation code is available in the GitHub repository. Several functional correlation between age and knowledge have been simulated, and the model used in the analysis - which includes age as a ordinal categorical predictor of knowledge with monotonically increasing effect - has been able to recover the different shapes. Causal effect of activities, family composition and schooling have been simulated and tested.

The simulated data have been used - albeit in a previous version - to estimate the minimum number of interviewees necessary to recover the parameter values. If individuals were to name a maximum of 300 items in the freelist, 50 interviewees would have been sufficient to obtain reliable estimates of the parameters. Given that data collection in vivo is much less regular and less controllable than in silico, we roughly doubled the number of interviewees and that of questions.

9.8 Dimension analysis

Multidimensional IRT analyses can be used to assess the dimensionality or underlying latent variable structure of a measurement. Its results are comparable to those of a Factor Analysis, but IRT have several advantages, in particular they allow the latent individual trait and the question parameters to vary independently, whereas in Factor Analysis item difficulty is assessed as a function of the abilities of the sample, and the abilities of respondents are assessed as a function of item difficulty (Osteen, 2010). To test for dimensionality in our knowledge measure, we run the model described in the main text and above (equations S3, S4 and equation 3 in main text) forcing it to separate knowledge into multiple dimensions, from 1 to 5. We then calculated the WAIC values of each of these model fits to estimate how well they fit the data and compared them. WAIC values measure how accurately a model can predict new data, and are widely applied for model comparison. A model with lower WAIC value can make better estimates out of sample. When we compare WAIC values for models fit to different number of dimensions, we can expect an improvement in the WAIC score if adding a new dimension helps describe structure in the latent variable, i.e. helps explain variation. In figure S11 are shown WAIC values for models with one to five dimensions, divided by type of question (freelists, questionnaire and image recognition). This is because the structure of knowledge as described by the three different data types is different. The results from the questionnaire, in the middle panel, indicate no underlying structure, as the model with one dimension ('age_1') performs best: it has lower WAIC score and none of the models including more dimensions perform similarly well. Results from freelist and image recognition, instead, show some signs that including more dimensions helps to better describe variation in knowledge. In particular, an image recognition model with three dimensions ('age_3' in the right panel) seems to best describe the data, and four or five dimensions perform similarly well. For freelists, increasing the number of dimensions keeps improving the fit of the model ('age_5' with five dimensions in the left panel has the lowest WAIC score, and models with four or three dimensions follow). This suggests that knowledge, the latent variable in our analysis, is structured in multiple dimensions, and that the different types of data are not equally good at allowing this structure to emerge (Supplementary section 9.4.4 offers some more insight on how data collection procedures can influence the results, especially in terms of dimensionality). It is not necessarily clear, though, which number of dimensions better describes the data. We hence approached the problem mainly descriptively and compared the results from the different models with up to 5 dimensions of knowledge.

Figures S12, S13 and S14 show the patterns of knowledge variation when subsetting knowledge in two, four and five dimensions respectively, and can be compared with figure 5 that shows results from a three dimensional model. From a visual inspection, we can see that three main patterns tend to be repeated, as described in the main text: a dimension in which both sexes learn at similar speed (dimension 1), one in which boys learn more than girls (dimension 2) and some remaining variation (dimension 3). If more than three dimensions are present, some of these patterns are repeated, so that for example, in four dimensions, there are two different dimensions that describe remaining variation. Based on these results we decided to describe three dimensions as the most helpful in order to tackle the subject of knowledge specialization.

In this process, though, interpreting the real life implications of these dimensions would be very important. Although our analysis was not developed with the scope of analyzing differences between question items, we can have a look at which are the most important items in each dimension - listed in the freelist - by looking at the question parameters. In particular, we seem to have interesting results looking at the items listed in the freelist for which the difficulty parameter b_j is lower can help us understand which items are considered more salient in each dimension. For example, the ten easier items in the dimension where both sexes learn at the same rate include mainly courtyard animals such as chicken and goats. The most salient items in the dimension where only males learn are mainly fish and wild birds, which are more relevant for boys who go hunting and fishing. To better understand how these dimensions correlate with different areas of knowledge, we should run analyses that can let differences between hypothesized groups of similar content emerge from the data (i.e. including predictors for question level parameters).

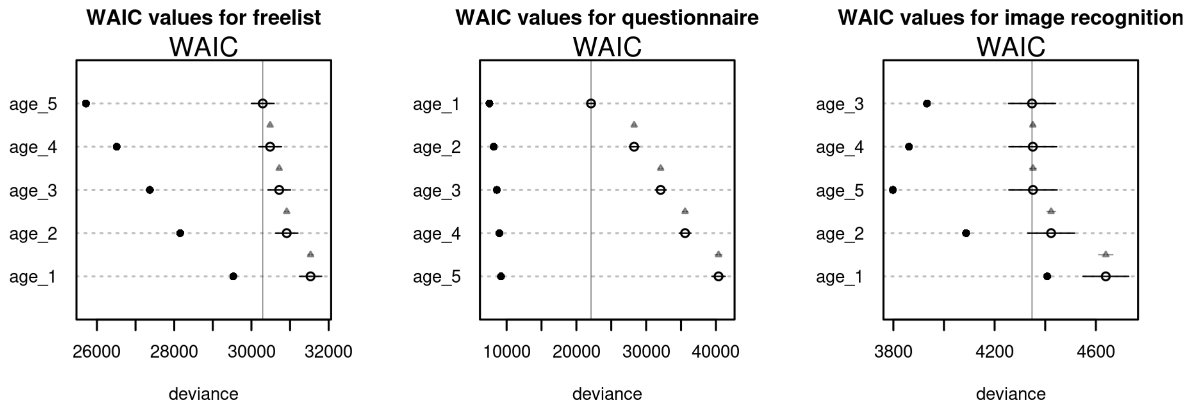

Figure S11: Comparison of WAIC values between models with variable number of dimensions, from 1 to 5. The first panel to the left is relative to freelist questions only, the middle refers to questionnaire results and the left panel is for image recognition. The filled points are the in-sample deviance values. The open points are the WAIC values. The line segments show the standard error of each WAIC. The lighter line segment with the triangle on it is the standard error of the difference in WAIC between the models.

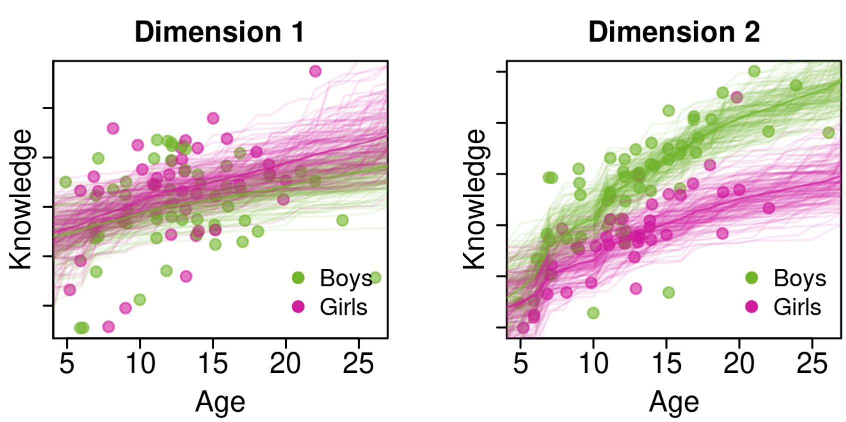

Figure S12: Individual knowledge K_i and predicted values by age and sex in two dimensions.

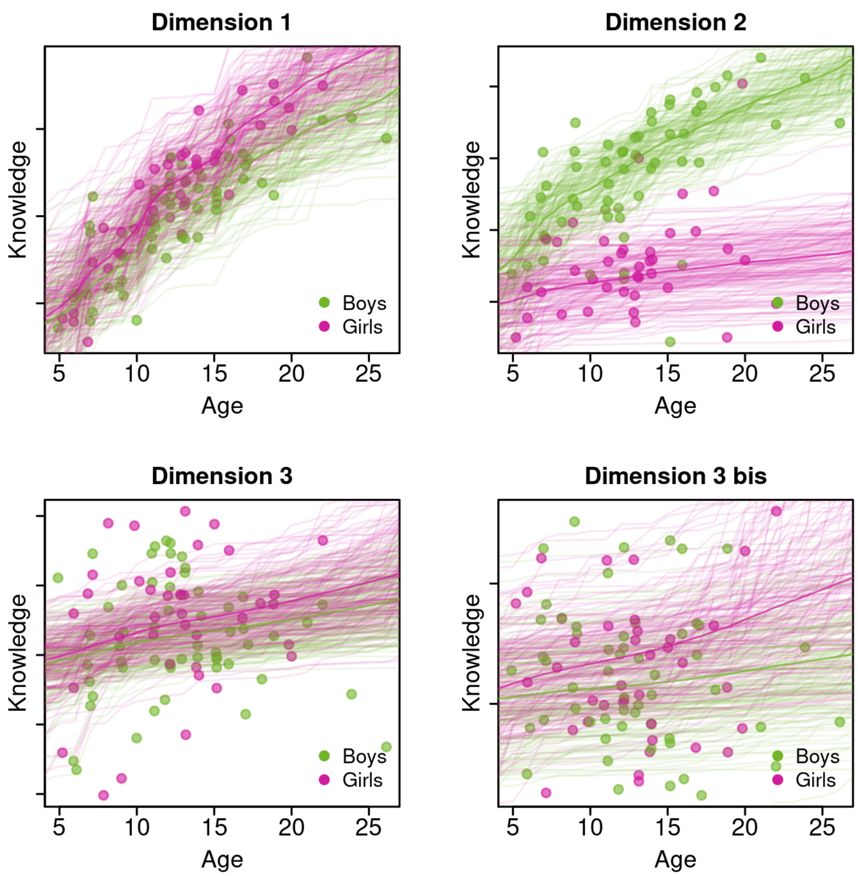

Figure S13: Individual knowledge K_i and predicted values by age and sex in four dimensions.

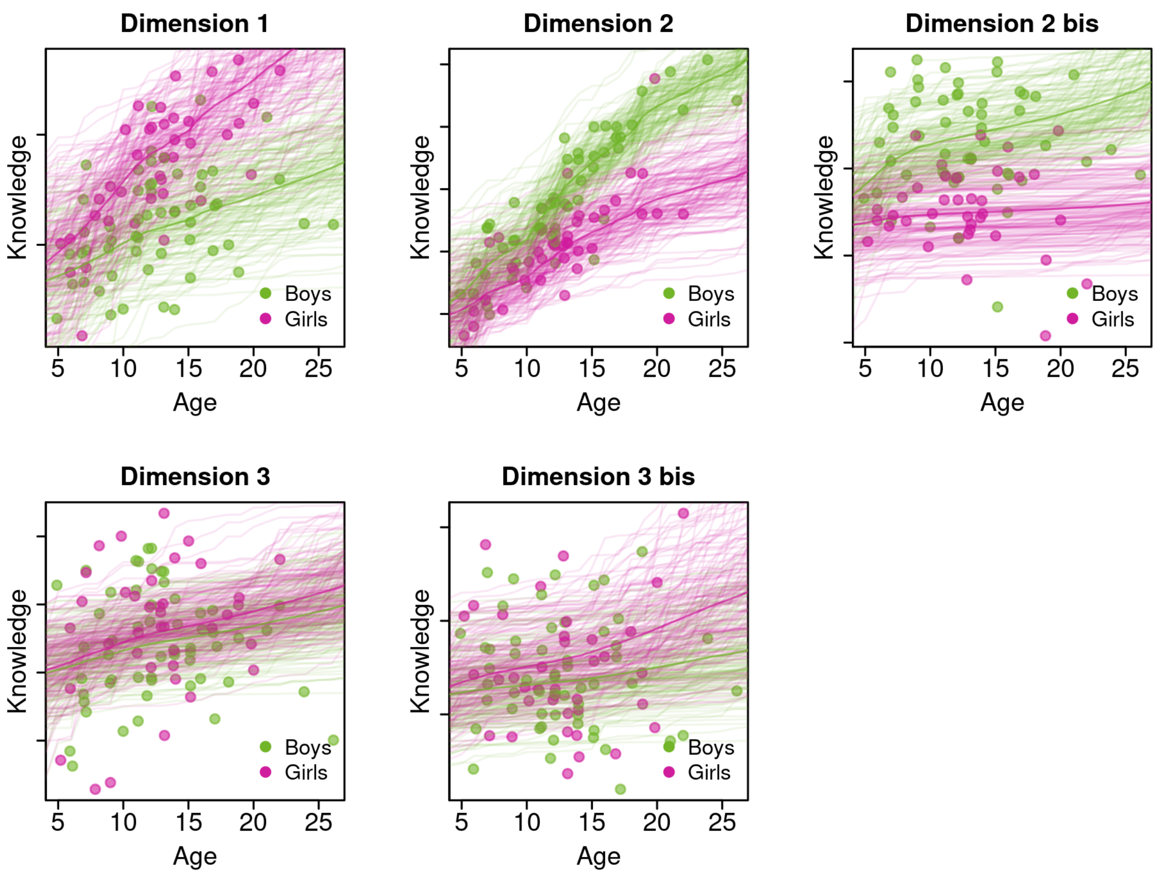

Figure S14: Individual knowledge K_i and predicted values by age and sex in five dimensions.

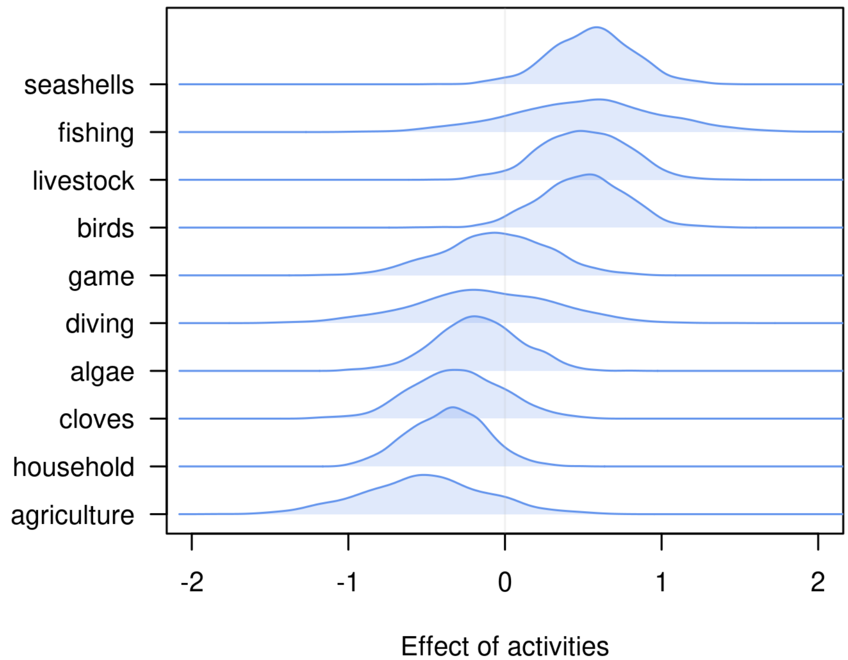

Figure S15: Posterior distribution of effect of each activity.

9.9 Other factors influencing knowledge

In the main text of the article we presented some results on the causal effects of some factors influencing knowledge. Here we will describe these results more in detail and present some plots that help discuss them.

9.9.1 Activities

Activities practiced are an important element for the development of knowledge. In the main text we saw that practicing an activity can shift the expected age for an individual of a certain knowledge of even more than one decade (see figure 6). Figure S15 shows the posterior distribution of the effects of each activity. We also mentioned that, once controlled by activities practiced, the difference in knowledge between sexes seems to disappear. Figure S16 shows estimated knowledge by age and sex, controlling for activities. Notice that the distribution of the lines is mostly overlapping.

9.9.2 Family

As discussed in the main text, no clear theory exist on which aspects of the social environment are the most important for ecological knowledge.

Looking at the random effects for household (figure S17), there doesn't appear to be any strong difference between families. Some households might be slightly less knowledgeable, on average, but the effects are not strong. Something more specific could be more important, as families go.

Availability of models and sources of information for vertical and/or horizontal transfer is probably one of the most important aspects of it. In line with this expectation, presence of both parents in the household seems to have positive effect on knowledge of boys, but not of girls (see figure S18), who benefit from co-residing with mothers but seem to be penalized by the presence of fathers.

Other aspects of the family life seem to be less important. Birth order does not seem to have any effect (the total effect for birth order does not differ from zero and there not seem to be any direction

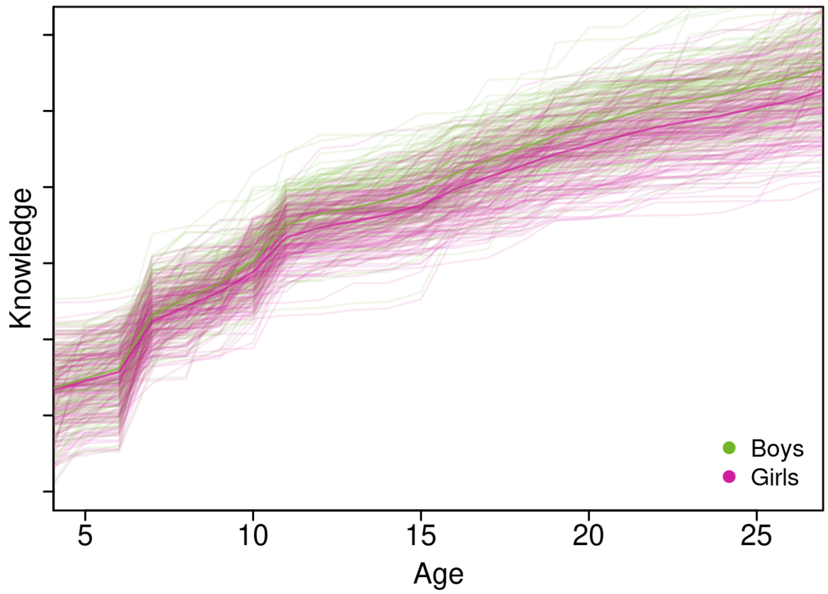

Figure S16: Knowledge estimated by age and sex, controlling for activities.

in the effect). Also, firstborns do not seem to have any advantage/disadvantage, which could be the case if the firstborn had differential access to the parents, or if a firstborn had responsibilities that could prevent from engaging in activities such as hunting birds.

But further analyses looking at shared knowledge within an household or along friends networks could give more interesting results.

9.9.3 Schooling

Schooling does not seem to have a strong effect on knowledge of the natural environment. Figure S20 shows how many years earlier (or later) would an individual who does not go to school reach the same knowledge as a 20 years old individual who attended the whole cycle. No strong effect seems to be present, although girls who do not attend school might have higher knowledge of those who do. This could mean that increasing schooling in rural areas would not impact local ecological knowledge acquisition. As an alternative explanation,the effect of schooling might not be visible because we did not subset to locally relevant ecological knowledge, especially in the freelist, but rather accepted any answer relative to animals and plants. So, for example, animals they could have learned of at school were also accepted, and might have replaced local ecological knowledge,

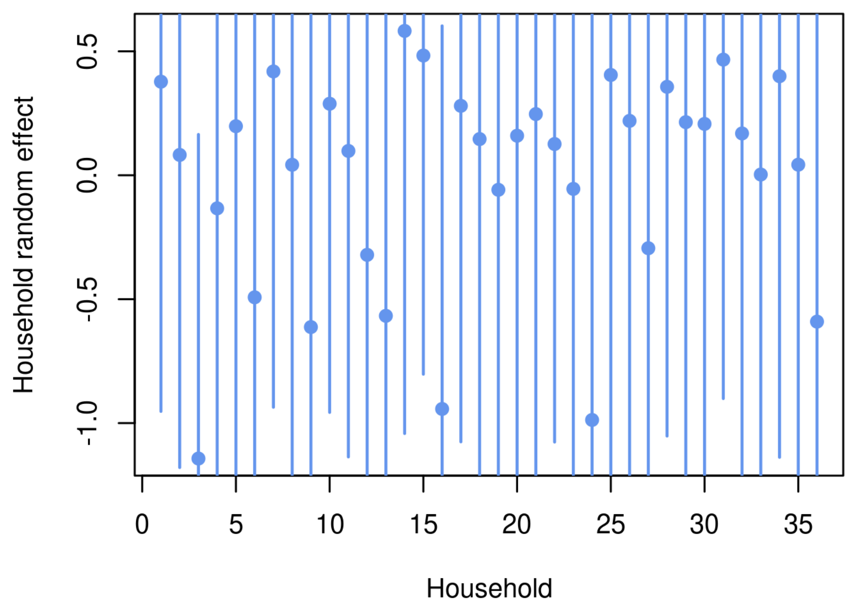

Figure S17: Random effects for families, from model 2, which includes age, sex and activities as other predictors

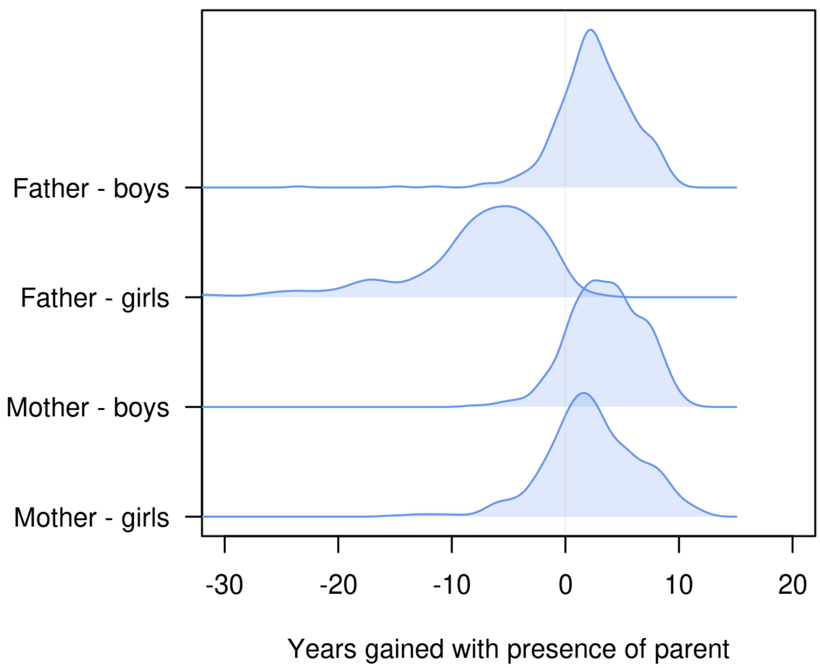

Figure S18: Distribution of years of knowledge gained thanks to the presence of parents, sex specific. Positive values indicate that the presence of one co-residing parent would allow an individual to reach earlier the same knowledge of a 20 years old individual who does not co-reside with a parent.

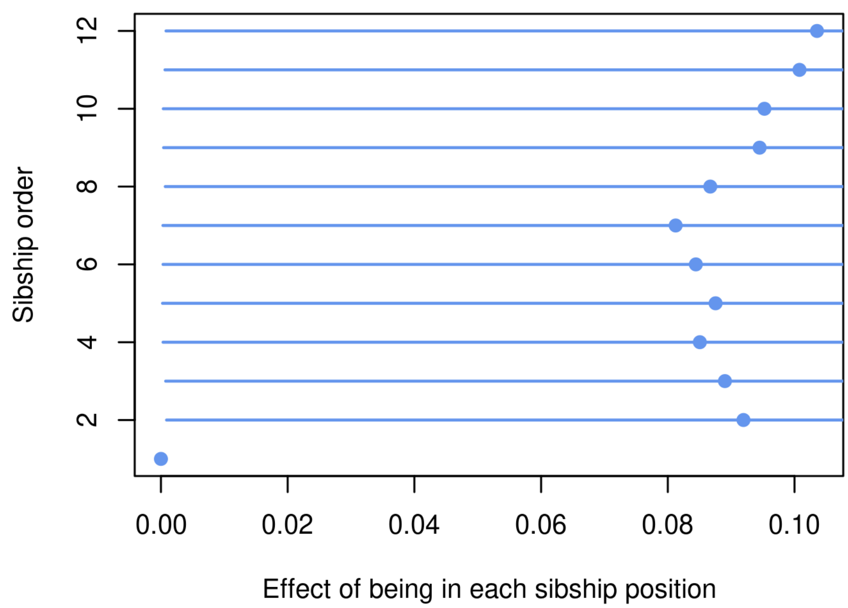

Figure S19: Birth order does not seem to have any effect on knowledge, as none of the positions in the sibship seem to have any different effect.

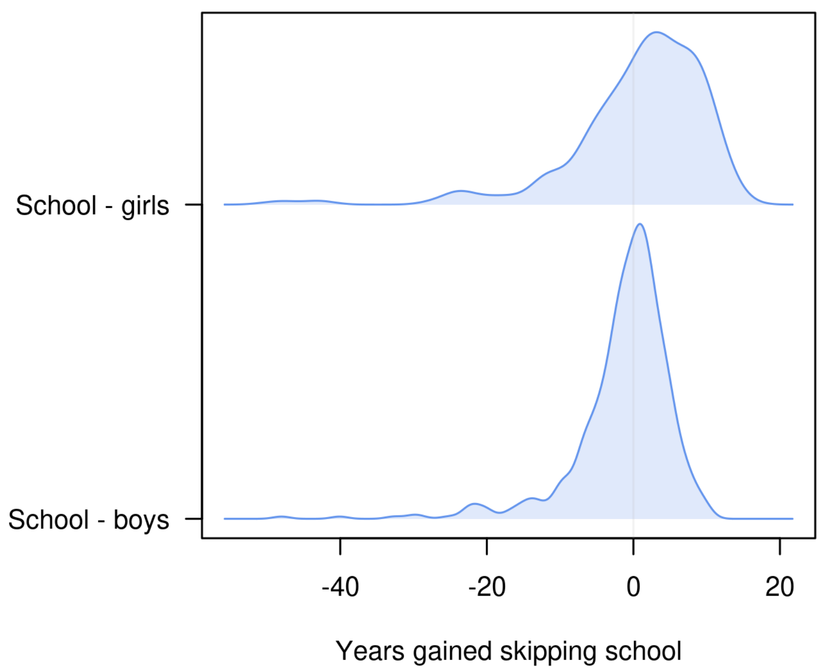

Figure S20: Distribution of years of knowledge gained by not going to school, sex specific. Positive values indicate that an individual who does not go to school would reach earlier the same knowledge of an individual who does.