



ARTICLE

<https://doi.org/10.1057/s41599-022-01066-y>

OPEN

 Check for updates

Do perceived control and time orientation mediate the effect of early life adversity on reproductive behaviour and health status? Insights from the European Value Study and the European Social Survey

Bence Csaba Farkas  ^{1,2,3}✉, Valérian Chambon⁴ & Pierre O. Jacquet  ^{1,2,3}

An association between early life adversity and a range of coordinated behavioural responses that favour reproduction at the cost of a degraded health is often reported in humans. Recent theoretical works have proposed that perceived control—i.e., people's belief that they are in control of external events that affect their lives—and time orientation—i.e., their tendency to live on a day-to-day basis or to plan for the future—are two closely related psychological traits mediating the associations between early life adversity, reproductive behaviours and health status. However, the empirical validity of this hypothesis remains to be demonstrated. In the present study, we examine the role of perceived control and time orientation in mediating the effects of early life adversity on a trade-off between reproductive traits (age at 1st childbirth, number of children) and health status by applying a cross-validated structural equation model frame on two large public survey datasets, the European Values Study (EVS, final $N = 43,084$) and the European Social Survey (ESS, final $N = 31,065$). Our results show that early life adversity, perceived control and time orientation are all associated with a trade-off favouring reproduction over health. However, perceived control and time orientation mediate only a small portion of the effect of early life adversity on the reproduction-health trade-off.

¹ Université Paris-Saclay, UVSQ, Inserm, CESP, 94807 Villejuif, France. ² Institut du Psychotraumatisme de l'Enfant et de l'Adolescent, Conseil Départemental Yvelines et Hauts-de-Seine, CH Versailles, 78000 Versailles, France. ³ LNC2, Département d'études Cognitives, École Normale Supérieure, INSERM, PSL Research University, 75005 Paris, France. ⁴ Institut Jean Nicod, Département d'études Cognitives, ENS, EHESS, CNRS, PSL Research University, 75005 Paris, France. ✉email: bence.farkas@ens.psl.eu

Introduction

Socioeconomic inequality is on the rise. In France, in 2016, the wealthiest 1% owned over 20% of the country's total wealth (Zucman, 2019). This metric has been steadily increasing since the 1980s and similar or even more extreme trends can be observed in the rest of Europe, China and the United States (Piketty and Saez, 2014; Zucman, 2019). Such drastic worldwide inequality leaves many people struggling with poverty and its consequences for many aspects of human life.

In fact, economic scarcity often comes together with other environmental factors that cumulatively contribute to reduced well-being and shorter lifespan (Pepper and Nettle, 2017). For that reason, these factors are collectively termed 'adversity'. Economic scarcity, violence and maltreatment, physical and affective instabilities within the family household, exposure to pollutants, or malnutrition, are all considered factors of adversity. When met early in life—that is, from conception to adolescence—these factors interfere with the developmental trajectories of many human biological systems, including growth and energy storage (Kuzawa et al., 2014), immunity (McDade, 2005; McDade et al., 2016), reproduction (Bar-Sadeh et al., 2020; Mell et al., 2018), cognition and behaviour (Ellis and Del Giudice, 2019). As a result, they can impact the functioning of these systems later in life (Miller et al., 2011; Smith and Pollak, 2021).

Compared to people who enjoyed affluent and stable environments during childhood, individuals who grew up in adverse environments are at greater risk of expressing obesity, type 2 diabetes, heart or respiratory diseases, cancers, or autoimmune diseases later in life (Hughes et al., 2017; Miller et al., 2011). Paradoxically, they also produce behaviours that can be equally detrimental for their health: they smoke more (Legleye et al., 2011; Melotti et al., 2011; Nandi et al., 2014), use cannabis (Legleye et al., 2011) and alcohol more (Melotti et al., 2011; Nandi et al., 2014), and exercise less (Nandi et al., 2014). In parallel, early exposure to adverse environments appears to direct individuals toward an urgent need to achieve reproductive goals through physiological and behavioural processes leading to early puberty (Amir et al., 2016), early entry into sexual life and parenthood (Nettle et al., 2011) along with a greater number of children (Nettle, 2010).

An possible explanation for the asymmetry between maintenance and reproductive goals is that of an energy trade-off between these two competing functions (Ellis and Del Giudice, 2019; Nettle and Frankenhuys, 2019). This explanation borrows from Life History theory (Del Giudice et al., 2015; Hill and Kaplan, 1999), a general framework in evolutionary biology that highlights the limited nature of bioenergetic resources and the resulting trade-offs that bind phenotypic traits into patterns of co-variation. It puts forward the idea that investments of resources in reproductive efforts are accompanied by decreases in health efforts on the one hand and direct maintenance costs on the other hand. Ultimately, this pattern would lead to poorer health status later in life and shorter life-expectancy. Interestingly, there may be a notable difference in this pattern between the two sexes (Sear, 2020). For men, poorer health status could be primarily the result of maintenance costs associated with poor health efforts, whereas for women it could additionally be caused by the high metabolic expenditures required by pregnancy and parental care during offspring's early life (Jasienska et al., 2017; Ryan et al., 2018).

Why would adversity lead people to prioritise reproduction and sacrifice their own health and well-being? One possibility is that such a strategy forms the present-oriented end of a behavioural trade-off between present time and future time (Pepper and Nettle, 2017). Individuals exposed to adversity may have less perceived or actual control over their own lives (i.e., external

events that cause mortality and morbidity are beyond their control) and thus may prefer acting on a day-to-day basis in order to receive payoffs sooner. This phenomenon, known as "collection risk", describes situations in which waiting for the collection of a later reward—that is, planning for the future—is not optimal because it is not certain that you will stay in good enough condition to benefit from it (Stevens and Stephens, 2010). Moreover, by delaying reward collection, individuals also potentially expose themselves to "waiting costs", that is, to losing the benefits that could have been accrued in the delay (Mell et al., 2021).

Using either mechanism, this framework predicts that perceived control and time orientation should be key variables mediating the relationships between early life adversity and the trade-off between maintenance and reproduction. Thus, for individuals who have little or no control over events that may affect their lives, the future is uncertain and, therefore, they cannot risk delaying reproduction to invest in activities or functions that are only beneficial in the long run, such as health in old age. Recent findings provide evidence that seem to support this prediction, at least in the health domain. First, the link between life conditions and perceived control—and more broadly locus of control, i.e., the degree to which individuals believe that they, as opposed to external factors such as chance, fate, or other agents, have control over their lives (Lefcourt, 1976; Rotter, 1966)—is well documented. For example, a number of studies have shown that people of lower social class, in possession of fewer resources, exposed to greater instabilities, or in a poorer health status, tend to perceive external, uncontrollable forces and other individuals as the primary causes of events that affect their lives (reviewed in Kraus et al., 2012). In contrast, people with higher socioeconomic position perceived themselves (their internal states, motivations and emotions) as the primary causal sources of what happens to them (Kraus et al., 2012). In addition, Pepper and Nettle (2014) found that the effect of individuals' socioeconomic status (SES) on the amount of self-reported health effort was entirely mediated by perceived extrinsic mortality risk. Some recent works also suggest that certain adversity factors encountered early in life (e.g., economic scarcity, attachment insecurity) increases mental health problems (e.g., depression, anxiety) later in life via an external locus of control (Culpin et al., 2015; Di Pentima et al., 2019). Finally, there is also extensive evidence that exposure to harsh and unpredictable childhood environments induces people to adopt an unpredictability schema, a pervasive belief that the world and people are unpredictable, chaotic and untrustworthy (Cabeza de Baca and Ellis, 2017; Ross and Hill, 2002). Multiple aspects of such schemas have been investigated in relation to early life experiences and later life risky behaviours. For example, future discounting was found to mediate the effects of family unpredictability on risk taking (Hill et al., 2008), and maternal parental and mating efforts were systematically related to a composite measure of unpredictability schemas (Cabeza de Baca et al., 2016).

To our knowledge, however, no existing studies has systematically explored the possibility that early life adversity, perceived control, time orientation, reproductive and maintenance traits all covary in a manner consistent with predictions made by theoretical frameworks inspired by Life History research (Pepper and Nettle, 2017; Ellis and Del Giudice, 2019). Yet, understanding how early life conditions shape the development of these traits along with their behavioural effects is extremely important for a number of reasons. It would allow a mechanistic understanding of the effects of early life adversity on different levels of an individual's biology and help to more accurately estimate the long-term consequences of such early life conditions on both physical and mental health. Importantly, it would also contribute

to recontextualizing the behaviour of less advantaged people as plastic and contextually appropriate responses to their local ecology, and not merely deregulated and dysfunctional responses to early life stress. Thus, improving our knowledge on these topics could further be used to help design innovative interventions in the educational or medical domains (Ellis et al., 2020). The present study therefore aims to progress towards these goals by conducting two sets of large-scale multivariate models testing the mediating role of perceived control (model set 1) and time orientation (model set 2) in the association between early life adversity and a hypothetical trade-off between reproductive (i.e., timing of reproduction, fertility) and maintenance (i.e., health status) traits. As these traits are expected to cluster differently between females and males (Sear, 2020), model sets will be run separately for individuals of both sexes. Each model set tests two main hypotheses. Hypothesis 1 suggests that early life adversity is related to the reproduction-maintenance trade-off. Hypothesis 2 suggests that early life adversity influences the reproduction-maintenance trade-off via perceived control (model set 1) or time orientation (model set 2). We predict that:

- i. Higher levels of early life adversity are associated with a reproduction-maintenance trade-off characterised by greater investment in reproductive activities (i.e., younger age at first reproduction, more children) and poorer health status.
- ii. This association is mediated by the individuals' perceived control/time orientation, such that higher levels of adversity decrease the feeling of control individuals have over their own lives/increase present orientation, and diminished control/increased present orientation in turn increases the need for individuals to put more resources in reproduction and fewer resources in health.

To verify our predictions and test their capacity to generalise to out-of-sample data, we apply multivariate structural equation modelling (Kline, 2015) and stratified k -fold cross-validation (Arlot and Celisse, 2010) on data from the European Value Study (EVS) and the European Social Survey (ESS). Both are large-scale, cross-national, and longitudinal survey research programmes on basic human values.

Methods

Samples of participants. The European Values Study (EVS) is a large-scale, cross-national, repeated cross-sectional survey research programme on basic human values. Its main topics are family, work, environment, perceptions of life, politics and society, religion and morality and national identity. The study has been conducted in four waves since 1981. We made use of the 4th wave of the survey, which started in 2008 and contains respondents from 46 European countries. The European Social Survey (ESS) is another large, cross-national and longitudinal survey that contains data from 40 countries on attitudes, beliefs and behavioural patterns. We made use of the 9th round of the survey that began in 2018. These survey waves contain data to assess respondents' childhood environments and to calculate the age of birth of their first child, both important life history related variables. From both datasets we removed respondents with too many missing values (+2 SDs from sample mean) and respondents with missing values on the age variable, as it cannot be accurately imputed. We also removed respondents without children, as both of our indicators of reproductive strategy (*Number of children* and *Age at 1st reproduction*) are only relevant for respondents with children. The final sample of the EVS data set consisted of 43,084 participants (25,341 females; 17,743 males). The final sample of the ESS data set consisted of 31,065

participants (17,639 females; 13,426 males). Descriptive statistics can be found in the Supplementary Table S1.

Missing data. Multiple imputation techniques were used to preserve sample size and avoid biased estimations of model parameters (see Supplementary Table S2 for the % of missing values per items). Twenty complete EVS datasets were generated by fully conditional specifications for categorical (logistic regression imputation) and ordinal data (proportional odds model). The mice package of R was used for imputation (van Buuren and Groothuis-Oudshoorn, 2011).

Multivariate models. The data were analysed with structural equation modelling (SEM) using the *lavaan* (Rosseel, 2012) and *semTools* (Jorgensen et al., 2020) packages in R. These models are made up of a 'measurement' model that relates the observed 'indicators' to hypothesised, but unobservable 'latents' and a 'structural' model that relates the latent variables to each other by specifying paths between them. The model we specified involved two latent variables: *Early life adversity* and *Reproduction-maintenance trade-off*. Additionally, *Perceived control* and *Time orientation* were directly measured by a variable of the EVS and ESS, respectively.

In our measurement models, *Early life adversity* is modelled as an emergent variable rather than a reflective latent variable (Brumbach et al., 2009; Mell et al., 2018). The rationale is that adverse life conditions or events are better conceptualised as factors that are not necessarily correlating with one another, but that all contribute to the cumulative probability of developing a particular outcome. Having been exposed to the death of a parent, having been raised in an economically deprived family or in a family with a low educational background, are factors that increase the probability of experiencing an adverse childhood environment, but that might be experienced relatively independently of each other. In addition, such factors might not contribute equally to the probability of developing a particular outcome. The SEM approach offers the opportunity to handle this problem using unknown weight composites, a procedure which captures the collective effects of a set of causes on a response variable (Grace and Bollen, 2008). In that case, the composite score is computed via a set of weights whose sum maximises the amount of variance explained in the dependent variables and thus allows comparing the relative contribution of the hypothesised causes to the overall predictive power of the composite. Here, the latent composite *Early life adversity* computes weights of three indicators based on their predictive power on the *Reproduction-maintenance trade-off* latent variable and the *Perceived control/Time orientation* variable.

In specifying the models, we chose to consider *Perceived control*, *Time orientation*, and *Health*—three variables that could be classified as ordinal—as continuous variables because responses measured on Likert scales with five or more points share many properties with continuous data and can occasionally be treated as such (Johnson and Creech, 1983; Norman, 2010).

EVS model. In more detail, the *Early life adversity* latent was modelled by three indicators (see Supplementary Table S2): *Economic capital deprivation*, *Human capital deprivation* and *Experienced mortality in childhood*. The *Economic capital deprivation* indicator was manually constructed from the respondents' scores on two items. Respondents were given the following context: 'When you think about your parents when you were about 14 years old, could you say whether...'. They were then asked to choose a response among 4 possible (from '1—Yes' to '4—No') on the following two statements: 'Parent(s)

had problems making ends meet' [variable v014] and 'Parent(s) had problems replacing broken things' [variable v018]. Item scores were recoded and summed such that greater scores indicate greater deprivation in economic capital. The *Human capital deprivation* indicator was calculated from six items from the same question set ('Mother liked to read books' [variable v011], 'Discussed politics with mother' [variable v012], 'Mother liked to follow the news' [variable v013], 'Father liked to read books' [variable v015], 'Discussed politics with father' [variable v016] and 'Father liked to follow the news' [variable v017]), plus two items providing information on the education of the respondents' parents ('Highest educational level attained father/mother (eight categories)' [variable v004E/V004R]). Item scores were recoded, *z*-scored and summed such that greater scores indicate greater deprivation in human capital. The *Experienced mortality* indicator was manually constructed by summing respondents' scores on the following binary items (Yes/No): 'Experienced: death of father' [variable u005a] and 'Experienced: death of mother' [variable u006a], at a reported age below 14. Item scores were recoded such that greater scores indicate greater mortality. Scores on the *Economic capital deprivation*, *Human capital deprivation* and *Experienced mortality* indicators were *z* transformed and normalised to be between 0 and 10, before entering them into the model.

The *Reproduction-maintenance trade-off* latent variable was modelled by three indicators (see Supplementary Table S2): *Age at 1st reproduction* (representing the timing of reproduction), *Number of children* (representing fertility), and *Health* (representing the maintenance state). The *Health* indicator was directly measured by the 'State of health (subjective)' [variable a009], asking respondents to answer the following question 'All in all, how would you describe your state of health these days?' by choosing a response among five possible, from '1—Very good' to '5—Very poor'. It is important to note that, although dependent on the subjective perception of the respondents, the subjective state of health is highly correlated with the objective somatic state. More specifically, the subjective assessment of health status predicts morbidity (Barger and Muldoon, 2006; Goldberg et al., 2001) and mortality (Benyamin and Idler, 1999; Idler and Benyamin, 1997) better than some traditional physiological risk factors (Haring et al., 2011; Jylhä et al., 2006). The *Age at 1st reproduction* indicator was constructed manually by subtracting the 'respondents birth year' [variable x002] from the 'birth year of the first child' [variable x011_02]. The *Number of children* indicator is directly measured by 'How many children do you have—deceased children not included' [variable x011_01]. A residual covariance term was also introduced between the *Age at 1st reproduction* and *Number of children* indicators in order to account for the effect of early reproduction on the total number of children reported at the time of the interview. Greater scores on the latent variable indicate a poorer health status, a younger age at 1st childbirth, and a greater number of children.

Finally, *Perceived control* was measured directly by the variable 'How much freedom of choice and control' [variable a173] (see Supplementary Table S2). Respondents were put in the following context: 'Some people feel they have completely free choice and control over their lives, and other people feel that what they do has no real effect on what happens to them.' They then ask to answer the question 'How much freedom of choice and control you feel you have over the way your life turns out?', choosing one value in a ten points scale, from '1—None at all' to '10—A great deal'. A greater score on this item therefore indicates a greater sense of control over life events.

Whereas *Reproduction-maintenance trade-off* was modelled as a latent variable and was scaled by fixing its variance to 1, based on the recommendation of Brumbach et al. (2009). *Early life*

adversity was modelled as a composite latent variable. As composite variables also need to be scaled for identification purposes by fixing the coefficient of one of the causal indicators, *Early life adversity* was scaled by setting the path from *Economic capital deprivation* to 1.

In our structural model, we specified three paths: a path between *Early life adversity* and *Perceived control*, a path between *Perceived control* and *Reproduction-maintenance trade-off* and a path between *Early life adversity* and *Reproduction-maintenance trade-off*. This allowed us to test both the direct effect of adversity on allocation trade-offs, its indirect effect mediated by perceived control and the total effect, which is the sum of the direct and indirect effects.

ESS model. In this model, the *Early life adversity* latent was again modelled by the same three indicators (see Supplementary Table S2): *Economic capital deprivation*, *Human capital deprivation* and *Experienced mortality in childhood*. The *Economic capital deprivation* indicator was manually constructed from the respondents' scores on the items: 'Father's employment status when respondent 14' [variable EMPRF14, possible answers from '1—Yes employee' to '4—Dead/absent'], 'Father's occupation when respondent 14' [variable OCCF14B, possible answers from '1—Professional and technical occupations' to '9—Farm worker'] and 'Mother's occupation when respondent 14' [variable OCCF14B, possible answers from '1—Professional and technical occupations' to '9—Farm worker']. The variable 'Mother's employment status when respondent 14' [variable EMPRM14] was also initially considered, however, the extremely large number of missing values (46.77%) prevented its inclusion. Item scores were recoded, *z*-scored and summed such that greater scores indicate greater deprivation in economic capital. The *Human capital deprivation* indicator was manually constructed from the respondents' scores on the following variables: 'Highest educational level attained father' (seven categories) [variable EISCEDF] and 'Highest educational level attained mother' (seven categories) [variable EISCEDM]. Item scores were recoded and summed such that greater scores indicate greater deprivation in human capital. The *Experienced mortality in childhood* indicator was manually constructed by first creating two new variables by considering 'Dead/absent' responses to the 'Father's employment status when respondent 14' and 'Mother's employment status when respondent 14' items as indicators of absence. Item scores were recoded and summed such that greater scores indicate greater mortality. Scores on the *Economic capital deprivation*, *Human capital deprivation* and *Experienced mortality in childhood* indicators were *z* transformed and normalised to be between 0 and 10, before entering them into the model.

The *Reproduction-maintenance trade-off* latent was modelled by three indicators (see Supplementary Table S2): *Health*, *Age at 1st reproduction* and *Number of children*. The *Health* indicator was directly measured by Subjective general health [variable HEALTH], an item fully identical to its EVS counterpart. The *Age at 1st reproduction* indicator was constructed manually by subtracting the respondents birth year [variable YRBRN] from the birth year of their first child [variable FCLDBRN]. The *Number of children* indicator is directly measured by [variable NBTHCLD]. As for the EVS model, a residual covariance term was introduced between the *Age at 1st reproduction* and *Number of children* indicators. Greater scores on the latent variable indicate a poorer health status, a younger age at 1st childbirth, and a greater number of children.

Finally, *Time orientation* was measured directly by the item 'Plan for future or take each day as it comes' [variable PLNFTR] (see Supplementary Table S2), which provides 11 possible responses from '0—I plan for my future as much as possible' to

'10—I just take each day as it comes'. A greater score on this item therefore indicates a stronger present orientation.

As for the EVS model, *Reproduction-maintenance trade-off* was modelled as a latent and was scaled by fixing its variance to 1, and *Early life adversity* was modelled as a composite latent variable and was scaled by setting the path from *Economic capital deprivation* to 1.

In our structural model, we specified three paths: a path between *Early life adversity* and *Time orientation*, a path between *Time orientation* and *Reproduction-maintenance trade-off* and a path between *Early life adversity* and *Reproduction-maintenance trade-off*. These paths allowed us to test both the direct effect of adversity on allocation trade-offs, its indirect effect mediated by present vs future orientation, and the total effect, which is the sum of the direct and indirect effects.

Adjustment variables. The *Health*, *Age at 1st reproduction*, *Number of children*, *Perceived control* and *Time orientation* indicators present in the EVS model and/or the ESS model were adjusted for the effect of the age of the respondents and their level of household income [EVS: variable x047r; ESS: variable HINCTNTA] reported at the time of the interview (see Supplementary Table S2).

Fitting procedure. The models were fitted using a weighed least squares estimator (WLSMV) because of its robustness to deviations from normality. Model fit was assessed by the χ^2 , Comparative Fit Index (CFI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR) statistics. All these indicators are summary statistics of 50 individual fits obtained during cross-validation (see below). The χ^2 , CFI, RMSEA, and SRMR statistics were corrected by a scaling factor, which compensates for the average kurtosis of the data (Satorra and Bentler, 2001). A model's fit is generally considered excellent when the RMSEA is below 0.05, the CFI above 0.95 and SRMR below 0.08 (Hu and Bentler, 1999).

The same model was fitted separately for male and female respondents' data. We expected that the higher costs of reproduction for women might lead to more pronounced relationships. Separately estimating the model in the two genders allowed us to compare the relationships between genders as well as see whether the overall model fits are different, which would have important implications in itself. We will refer to the two models as the male and female models.

Importantly, for the ESS data set only, there are survey weights that needed to be incorporated to correct for estimates, standard errors, and chi-square-derived fit measures for the complex sampling design. We followed the recommended weighting procedure in R by the ESS methodological guide (https://www.europeansocialsurvey.org/docs/methodology/ESS_weighting_data_1_1.pdf). We then created a custom R script based on the lavaan.survey package to fit our model. For more details on this procedure, see Oberski (2014).

Cross-validation algorithm. To address the problem of overfitting due to the inherent complexity of SEM models (Breckler, 1990; Preacher, 2006; Roberts and Pashler, 2000), we employed a stratified k -fold cross-validation strategy (Arlot and Celisse, 2010). The aim of applying stratified k -fold cross-validation to SEM is twofold. First, it submits a model to sampling variability and therefore allows to estimate its stability across multiple reshuffling and re-stratification of the data sample. Second, it tests the capacity of a model to generalise its predictions to out-of-sample data. The analyses consisted of the following steps:

1. The full data set is randomly partitioned into five folds of nearly equal size.
2. Subsequently five iterations of training and validation are performed such that within each iteration a different fold of the data is held-out for validation (the test data, here representing 20% of the whole sample) while the remaining $k-1$ folds are used for fitting (the training data, here representing 80% of the whole sample).
3. At each iteration, the model is fitted on the training data, and then its parameters are set according to these results. After that, it is re-fitted on the test data.
4. The predictive value of the training model is further checked by applying the same cross-validation procedure on a test data set whose individual values have been randomly permuted within each indicator. The aim is to ensure that the fitted values obtained from modelling the training data failed at predicting the test data when its internal structure is broken down by means of randomisation. In other words, this procedure allows us to state whether the latent structure hypothesised by our structural equation model is present or absent in the training samples.
5. At the end of the five iterations, the whole sample is reshuffled and re-stratified before a new round of five iterations starts.
6. The whole procedure is repeated ten times (10 rounds of 5 iterations, meaning overall 50 iterations) in order to obtain reliable performance estimation (the mean and standard deviations across iterations of the predictive accuracy ratio). Note that at each iteration within a round, the training and the test datasets always include different data points.

Reporting of the results. Cross-validated goodness-of-fit indices for a given model are expressed in terms of the median on the testing data. Similarly, the goodness-of-fit indices of a given model are expressed in terms of the median on the training data. Finally, parameters estimates obtained from the measurement and the structural parts of a given model fitted on the training set over the 50 iterations are expressed in term of the median. The reason is that medians are best suited to account for a model's precision in the present context: the distributions of values are often skewed because of the sampling variability resulting from the multiple reshuffling and re-stratification of data during the cross-validation procedure. Comparisons were made by using Wilcoxon rank sum tests. Finally, to enhance the readability of the text, all statistical indices and parameter estimates corroborating the description of the models are reported in the tables included in the main text and in the Supplementary Information. The cross-validated median goodness-of-fit indices are reported in Tables 1 and 2. The median parameter estimates of their 'measurement' and 'structural' parts are reported in Table 3 for the EVS data set, and Table 4 for the ESS data set.

Visualising the models. Visualising the modelled individual latent scores is difficult because in our cross-validation strategy, the data set at each iteration has a different number and identity of subjects. Therefore, simply averaging across iterations is impossible. So, we resorted to ignoring cross-validation for visualisation purposes and merely estimated the model on each imputation. Then, we used the *lavaanPredict* function to extract the modelled variable scores for each subject. Finally, we averaged these results across the 20 imputed datasets. The associations between the *Early life adversity* scores and the *Perceived control/Time orientation* scores, so as the associations between the *Perceived control/Time orientation* scores and the *Reproduction-*

Table 1 EVS models.

Data	Index	EVS Male model	EVS Female model
Training	χ^2	188.684 (12.190)	340.798 (17.489)
	CFI	0.964 (0.003)	0.965 (0.002)
	RMSEA	0.038 (0.001)	0.043 (0.001)
	SRMR	0.016 (<0.001)	0.018 (0.001)
Test	χ^2	63.966 (15.528)	87.626 (14.718)
	CFI	0.970 (0.012)	0.972 (0.007)
	RMSEA	0.020 (0.004)	0.022 (0.003)
	SRMR	0.020 (0.003)	0.021 (0.002)
Random	χ^2	783.909 (50.387)	1284.649 (58.340)
	CFI	0.000 (0.000)	0.000 (0.000)
	RMSEA	0.091 (0.003)	0.098 (0.003)
	SRMR	0.072 (0.003)	0.077 (0.002)

Stratified fivefold cross-validation. Values are medians over 50 iterations, values in brackets are median absolute deviations.

maintenance trade-off latent scores were visualised in Supplementary Figs. S1 and S2.

Mixed-effects models of Perceived control and Time orientation. As discussed below, visualising the relationships between the constructs of our structural model revealed an interesting non-linearity. In order to quantify this, we ran an exploratory series (8 series: 2 gender \times 2 associations \times 2 surveys) of three mixed-effects models (using a maximum-likelihood estimator) that we compared by means of likelihood ratio tests (using the *lme* function of the *nlme* R package, Pinheiro et al., 2022). While all three models of a series included random subject intercepts, the 1st one modelled the association of *Perceived control* and *Time orientation* with *Early life adversity* or with *Reproduction-maintenance trade-off* as a linear function, the 2nd one and the 3rd one modelled it as degree 2 and degree 3 polynomials, respectively.

Control analyses for respondents without children. In addition, to make sure that the exclusion of respondents without children did not bias our results, we carried out a set of control analyses. We reran each model, using the exact same pipeline, except that for these analyses we did not exclude childless subjects. Instead, we manually set the value on the *Number of children* variable to zero for such subjects and accounted for missing data in the *Age at 1st reproduction* variable by Full Information Maximum Likelihood (FIML, Enders and Bandalos, 2001). Since this method is only available when using a Maximum-Likelihood-based estimator, the only other difference was that we used the ML, instead of the WLSMV estimator for parameter estimation. These results are presented in Supplementary Tables S8, S9, S10 and S11.

Results

EVS data set

Cross-validated goodness of fit. Both the male and female models provided an excellent fit. This is supported by scaled CFI values > 0.95 , RMSEA values < 0.05 , and SRMR values < 0.08 on the test data set (Table 1 and Fig. 1a). These results indicate that the discrepancies between the observed covariance matrices on the test data and the model-implied covariance matrices on the training data were minimal (RMSEA), and that the models performed better than their null versions including only the variance of the indicators as parameters fitted on the test data (CFI, SRMR). This is also corroborated by the random fits, which show the degree to which the models failed to predict test data whose internal structure was decomposed using random permutations.

The model fits did not differ significantly between genders. The female models CFI (median_{females} = 0.972, median_{males} = 0.970, Wilcoxon $W = 1138$, $p = 0.165$) and SRMR (median_{females} = 0.021, median_{males} = 0.020, Wilcoxon $W = 1354$, $p = 0.992$) indices were not statistically different from their respective counterparts in the male models. However, they did have a higher RMSEA (median_{females} = 0.022, median_{males} = 0.020, Wilcoxon $W = 954$, $p = 0.010$).

Male model parameters. In the male model (Table 2 and Fig. 1b, c), the measurement model indicates that the composite *Early life adversity* impacts the other variables in the model primarily via *Human capital deprivation* and *Economic capital deprivation*. The contribution of *Experienced mortality* to the predictive power of the composite is much weaker, indeed not statistically significant. The *Reproduction-maintenance trade-off* latent variable positively correlates with the *Health* indicator and, to a lesser extent, negatively with the *Age at 1st reproduction* indicator, showing that male respondents with higher scores on this latent also report a poorer health status and reproduce earlier. *Number of children* on the other hand has no relationship with the latent. The structural model further indicates that *Early life adversity* is significantly and negatively related to *Perceived control*, meaning that in men, experiencing higher levels of early adversity is associated with a reduced sense of control over life events as an adult. *Perceived control* is also significantly and negatively related to the *Reproduction-maintenance trade-off* latent, suggesting that in men, a lower sense of control is associated with greater investments in reproduction to the detriment of health. Combining the above two, the estimate of the total and indirect effect of *Early life adversity* on *Reproduction-maintenance trade-off* indicates that the indirect effect is significant but accounts for a small portion of the total effect (~8.4%).

Female model parameters. In the female model (Table 2 and Fig. 1b, d), the measurement part indicates that the effect of the composite *Early life adversity* on the other variables of the model is primarily driven by *Human capital deprivation* and *Economic capital deprivation*. The contribution of *Experienced mortality*, on the other hand, is almost null. As for the male model, the *Reproduction-maintenance trade-off* latent variable correlates positively with the *Health* indicator and negatively with the *Age at 1st reproduction* indicator. However, unlike the male model, the strength of these two correlations is more homogeneous. In addition, the *Number of children* indicator also correlates significantly and positively on the latent. Therefore, female respondents who score high on the latent *Reproduction-maintenance trade-off* report poorer health, reproduce earlier and have more children. The structural part of the female model indicates that *Early life adversity* is significantly and negatively related to *Perceived control*, meaning that in women, higher levels of early adversity are associated with a reduced sense of control over their own lives. *Perceived control* is also significantly and negatively related to the *Reproduction-maintenance trade-off* latent, suggesting that in women, a lower sense of control is associated with greater investments in reproduction to the detriment of health. Combining the above two, the estimate of the total and indirect effect of *Early life adversity* on *Reproduction-maintenance trade-off* indicates that the indirect effect is significant but accounts for a small portion of the total effect (~4.5%). Comparing the male and female models reveals that all effects point in the same direction in both models. In the female model however, the relationship between the latent constructs and their indicators, as well as the relationships between these constructs, are stronger (or are equally strong) relative to the male model.

Table 2 EVS models.

Model part	Latent variables	Indicators	Unstd. est.	Cl	se	z	p	Std. est.
Measurement model	Early life adversity	<-	Economic capital deprivation	1.000 [1.000, 1.000]	0	-	-	0.660
	Early life adversity	<-	Human capital deprivation	1.429 [1.082, 1.779]	0.179	7.99	<0.001	0.599
	Early life adversity	<-	Experienced childhood mortality	0.417 [−0.018, 0.873]	0.226	1.88	0.060	0.094
	Health		Number of children	0.399 [0.333, 0.467]	0.034	11.83	<0.001	0.475
Reproduction-maintenance trade-off	=~	Age at 1st reproduction	-0.086 [−0.100, −0.072]	0.007	-12.08	<0.001	-0.181	
Reproduction-maintenance trade-off	=~	Number of children	0.013 [−0.018, 0.045]	0.016	0.83	0.405	0.013	
Reproduction-maintenance trade-off	=~	Early life adversity	-0.041 [−0.123]	0.005 [−0.050, −0.032]	-8.88 [−9.80]	<0.001	-0.095	
	Perceived control			0.013 [−0.147, −0.099]	-	<0.001	-0.261	
Structural model	Early life adversity	<-	Early life adversity	0.059 [0.046, 0.072]	0.007	8.96	<0.001	0.294
	Indirect effect	=~	$a * b$	0.005 [0.004, 0.006]	0.001	6.59	<0.001	0.025
	Total effect	=~	$c + (a * b)$	0.064 [0.050, 0.078]	0.007	9.13	<0.001	0.319
	Early life adversity	<-	Economic capital deprivation	1.000 [1.000, 1.000]	0	-	-	0.597
	Early life adversity	<-	Human capital deprivation	1.797 [1.549, 2.052]	0.130	13.82	<0.001	0.675
	Experienced childhood mortality		Number of children	0.187 [−0.081, 0.459]	0.138	1.38	0.169	0.041
Reproduction-maintenance trade-off	=~	Age at 1st reproduction	-0.108 [−0.121, −0.095]	0.017	16.77	<0.001	0.360	
Reproduction-maintenance trade-off	=~	Number of children	0.095 [0.072, 0.119]	0.007	-16.44	<0.001	-0.268	
Structural model	Early life adversity	<-	Early life adversity	-0.042 [−0.049, −0.036]	0.003	-12.41	<0.001	0.101
	Perceived control	<-	Perceived control	-0.116 [−0.137, −0.095]	0.011	-10.98	<0.001	-0.110
	Early life adversity	<-	Early life adversity	0.104 [0.089, 0.119]	0.008	13.38	<0.001	0.510
	Indirect effect	=~	$a * b$	0.005 [0.004, 0.006]	0.001	8.29	<0.001	0.024
	Total effect	=~	$c + (a * b)$	0.109 [0.093, 0.124]	0.008	13.51	<0.001	0.534

Parameter estimates. We also report under the z label values of Wald tests (and their p values) as indicators of simple effect sizes. All values are medians over 50 iterations.

Table 3 ESS models.

Data	Index	ESS Male model	ESS Female model
Training	χ^2	22.109 (5.225)	21.525 (4.508)
	CFI	0.993 (0.003)	0.996 (0.001)
	RMSEA	0.012 (0.002)	0.010 (0.002)
	SRMR	0.009 (0.001)	0.007 (0.001)
Test	χ^2	40.409 (13.522)	36.085 (10.366)
	CFI	0.971 (0.021)	0.989 (0.010)
	RMSEA	0.014 (0.007)	0.010 (0.006)
	SRMR	0.025 (0.004)	0.022 (0.003)
Random	χ^2	365.720 (61.269)	522.518 (71.897)
	CFI	0.000 (0.000)	0.000 (0.000)
	RMSEA	0.070 (0.007)	0.074 (0.006)
	SRMR	0.075 (0.005)	0.081 (0.004)

Stratified fivefold cross-validation. Values are medians over 50 iterations, values in brackets are median absolute deviations.

ESS data set

Cross-validated goodness of fit. Both the male and female models provide an excellent fit. This is supported by scaled CFI values > 0.95 , RMSEA values < 0.05 , and SRMR values < 0.08 on the test data set (Table 3 and Fig. 2a). These results indicate that the discrepancies between the observed covariance matrices on the test data and the model-implied covariance matrices on the training data are minimal (RMSEA), and that the models performed better than their null versions including only the variance of the indicators as parameters fitted on the test data (CFI, SRMR). This is also corroborated by the random fits, which show the degree to which models fail at predicting test data whose internal structure is broken down by means of random permutations. The model fits are overall better for the female models. The female models have significantly higher CFI (median_{females} = 0.989, median_{males} = 0.971, Wilcoxon $W = 613$, $p < 0.001$), lower SRMR (median_{females} = 0.025, median_{males} = 0.022, Wilcoxon $W = 2031$, $p < 0.001$) and RMSEA indices (median_{females} = 0.010, median_{males} = 0.014, Wilcoxon $W = 1883$, $p < 0.001$).

Male model parameters. In the male model (Table 4 and Fig. 2b, c), the measurement model shows that none of the three indicators of the composite *Early life adversity* has a convincing predictive weight on the other variables of the model. However, the *Reproduction-maintenance trade-off* latent variable shows a good consistency in this male model, with respect to its EVS counterpart. Indeed, the latent correlates positively with the *Health* indicator, negatively with the *Age at 1st reproduction* indicator, and positively with the *Number of children* indicator. Therefore, male respondents who score high on the latent *Reproduction-maintenance trade-off* report a poorer health, reproduced earlier, and have more children. The structural model confirms that *Early life adversity* is not significantly related to either *Time orientation* or *Reproduction-maintenance trade-off*. It shows however that *Time orientation* is significantly and positively related to the *Reproduction-maintenance trade-off* latent, suggesting that in men, more present orientation is associated with greater investments in reproduction to the detriment of health. Given the complete absence of effects of *Early life adversity* in this model, the indirect and total effects are not discussed.

Female model parameters. In the female model (Table 4 and Fig. 2b, d), the measurement part indicates that the predictive power of the composite *Early life adversity* is driven by *Human capital deprivation*, *Economic capital deprivation* and *Experienced*

mortality to similar extents. As for the male model, the *Reproduction-maintenance trade-off* correlates in a consistent way with each of its 3 indicators as well. Indeed, female respondents who score high on this latent report a poorer health, reproduced earlier, and have more children. The structural model further indicates that *Early life adversity* is significantly and positively related to *Time orientation*, meaning that in women, greater levels of adversity are associated with a more present-oriented worldview. *Time orientation* is also significantly and positively related to the *Reproduction-maintenance trade-off* latent, suggesting that in women, a stronger orientation towards the present is associated with greater investments in reproduction to the detriment of health. Putting the above two together, the estimation of the total and indirect effect of *Early life adversity* on *Reproduction-maintenance trade-off* indicates that the indirect effect is significant but represents a small part of the total effect (~2.9%). Overall, comparing the male and female models reveals that most effects point in the same direction. The female model, however, overall has larger or equal effect sizes in all relationships. This is true both for the measurement and structural models.

Nonlinear effects of perceived control and time orientation. Visualising the relationships between the latent constructs of the EVS and ESS male and female models reveals an interesting and unexpected pattern (see Supplementary Figs. S1 and S2): whereas there is an approximately linear decrease in the *Reproduction-maintenance trade-off* and *Early life adversity* latent scores with increasing *Perceived control* and *Time orientation* scores, this trend seems to break somewhat at more extreme values of the latter variables, especially for women. In order to quantify these effects we ran a series of exploratory mixed-effects models. These post-hoc analyses first revealed that, for both males and females, the model that best fitted the association of *Perceived control* with *Early life adversity* as well as with *Reproduction-maintenance trade-off* was a degree 3 polynomial (cubic) model that included linear, quadratic and cubic terms as fixed-effects (see Supplementary Tables S4 and S5). Similarly, for both males and females, the model that best fitted the association of *Time orientation* with *Early life adversity* as well as with *Reproduction-maintenance trade-off* was a degree 2 polynomial (quadratic) model that included both a linear and a quadratic term as fixed-effects (see Supplementary Tables S6 and S7).

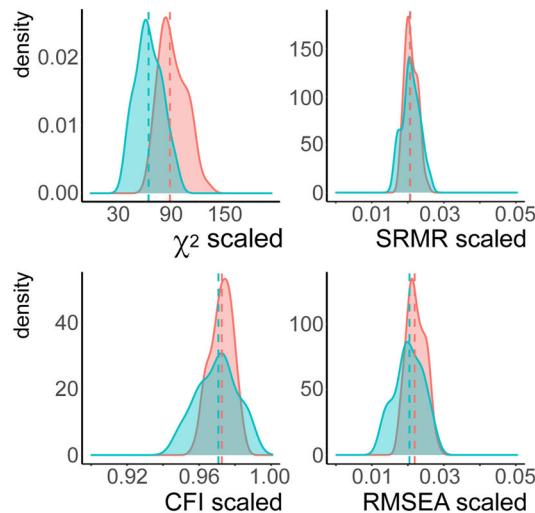
Control analyses for respondents without children. To make sure that our results were not biased by our initial decision to exclude respondents without children from the analyses, we carried out a set of control analyses, in which we included childless respondents and used FIML to also include these partially complete cases during parameter estimation. The inclusion of childless respondents led to larger sizes of the EVS (females: $N = 34,510$; males: $N = 27,414$) and ESS (females: $N = 23,941$; males: $N = 20,584$) samples. Both the EVS and ESS control models had extremely similar goodness of fit indices to our main results (Supplementary Tables S8 and S10). Parameter estimates in the female models were also qualitatively unchanged (Supplementary Tables S9 and S11). The only notable differences were observed in the male models in both datasets. In the EVS control male model, the association between the *Reproduction-maintenance trade-off* latent and the *Number of children* indicator became statistically significant. In the ESS control male model, we also observed a number of changes. The contribution of *Experienced mortality* to the *Early life adversity* composite became statistically significant, which suggests that in our main models, the absence of such a contribution was due to the lack of positive cases on the *Experienced mortality* variable. The positive

Table 4 ESS models.

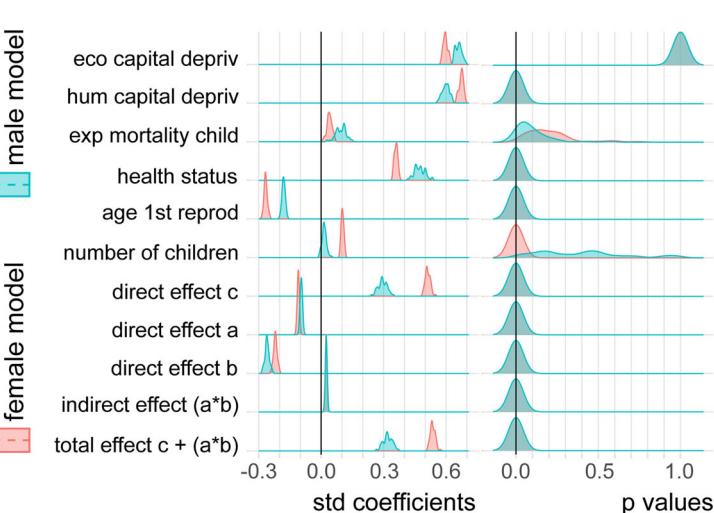
ESS Male model	Model part	Latent variables	Indicators	Unstd. est.	Cl	se	z	p	Std. est.
Measurement model	Early life adversity	<~	Economic capital deprivation	1.000	[1.000, 1.000]	0	-	-	0.357
	Early life adversity	<~	Human capital deprivation	1.127	[-0.429, 2.722]	0.787	1.42	0.155	0.572
	Early life adversity	<~	Experienced childhood mortality	1.801	[-0.295, 3.685]	0.993	1.66	0.098	0.562
	Health	0.128	[0.069, 0.193]	0.031	4.33	<0.001	0.164	-0.248	
Reproduction-maintenance trade-off	Age at 1st reproduction	=~	Number of children	0.162	[0.064, 0.258]	0.050	3.19	0.001	0.176
Reproduction-maintenance trade-off	Time orientation	=~	Early life adversity	0.024	[-0.006, 0.054]	0.015	1.55	0.122	0.041
Reproduction-maintenance trade-off	(a) Time orientation	=~	Time orientation	0.098	[0.041, 0.147]	0.027	3.39	<0.001	0.259
Structural model	Early life adversity	=~	Early life adversity	0.068	[-0.009, 0.145]	0.040	1.72	0.086	0.300
	Indirect effect	=~	$a * b$	0.002	[0.000, 0.006]	0.002	1.41	0.158	0.010
	Total effect	=~	$c + (a * b)$	0.070	[-0.009, 0.151]	0.041	1.73	0.084	0.314
	Early life adversity	<~	Economic capital deprivation	1.000	[1.000, 1.000]	0	-	-	0.416
	Early life adversity	<~	Human capital deprivation	1.101	[0.400, 1.771]	0.349	3.10	0.002	0.652
	Experienced childhood mortality	<~	Experienced childhood mortality	0.990	[0.339, 1.647]	0.331	2.92	0.003	0.380
	Health	0.173	[0.134, 0.212]	0.020	8.68	<0.001	0.213	-0.400	
Reproduction-maintenance trade-off	Age at 1st reproduction	=~	Number of children	0.198	[0.128, 0.267]	0.035	5.57	<0.001	0.208
Reproduction-maintenance trade-off	(a) Time orientation	=~	Early life adversity	0.033	[0.010, 0.057]	0.012	2.76	0.006	0.049
(b) Reproduction-maintenance trade-off	Time orientation	=~	Time orientation	0.087	[0.058, 0.115]	0.014	5.96	<0.001	0.228
(c) Reproduction-maintenance trade-off	Early life adversity	=~	Early life adversity	0.097	[0.050, 0.144]	0.024	3.99	<0.001	0.366
Indirect effect	Total effect	=~	$a * b$	0.003	[0.001, 0.005]	0.001	2.49	0.013	0.011
		=~	$c + (a * b)$	0.100	[0.052, 0.148]	0.025	4.01	<0.001	0.378

Parameter estimates. We also report under the z label values of Wald tests (and their p-values) as indicators of simple effect sizes. All values are medians over 50 iterations.

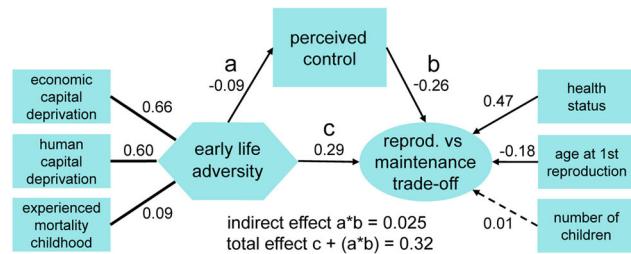
a. EVS models. Cross-validated fit indices



b. EVS models. std coeff and p values proba densities



c. EVS male model. Training data



d. EVS female model. Training data

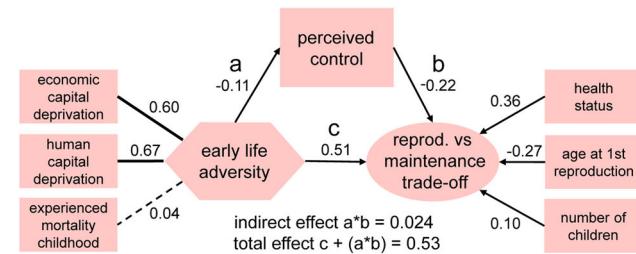


Fig. 1 EVS models. Main results. **a** Distributions of the goodness-of-fit indices of the male and female models cross-validated on the test datasets. Vertical lines indicate the median. **b** Distributions of the standardised coefficients and associated *p*-values of the indicators (see rectangles in panel **c**) estimated from fitting the model to the training datasets. The indirect effect represents the part of the effect of *Early life adversity* on the *Reproduction-maintenance trade-off* that is routed through *Perceived control*. **c, d** Structures and standardised parameters (median values) of the male (**c**) and female (**d**) models estimated from fitting the training datasets. Ellipses represent latent variables, rectangles represent their indicators, composite variables and direct measures. Significant paths are represented by bold lines and arrows.

relationship between *Early life adversity* and *Time orientation*, and between *Early life adversity* and the *Reproduction-maintenance trade-off* also reached the conventional significance level. As a result, so did the overall indirect and total effects. Effect sizes in all models also tended to be larger in the control models. Thus, these control analyses indicated that our findings are robust to the inclusions of childless subjects.

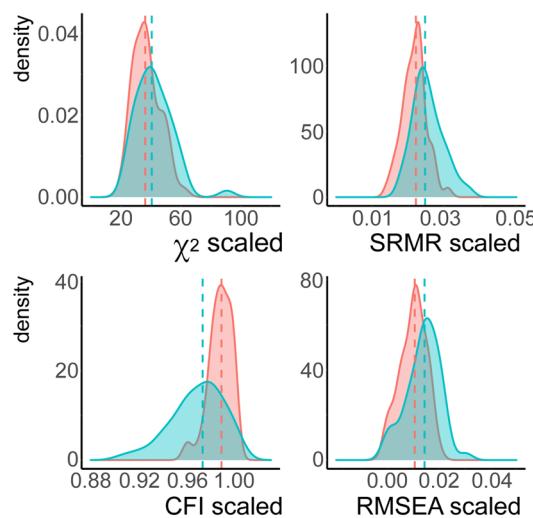
Discussion

In this study, we investigated two psychological traits—perceived control and time orientation—that possibly mediate the effect of early life adversity on reproductive behaviour and health status. To do so, we made use of a cross-validated structural equation modelling analysis on a large, public survey database, the European Values Survey (EVS). Confirming previous studies (Brumbach et al., 2009; Mell et al., 2018; Nettle, 2011), we found that deprivation in human and economic capital is associated with poorer health, earlier reproduction and a higher overall number of children. Importantly, our models also revealed a moderate effect of perceived control on the shape of a hypothetical trade-off between reproductive and maintenance traits. However, the effect of early life adversity on perceived control was small. The effect of current income on this psychological trait was of a similar magnitude, suggesting that the ecological factors (past or current) that we used here are only weak proxies for the experiences that actually influence this trait. Indeed, the accurate

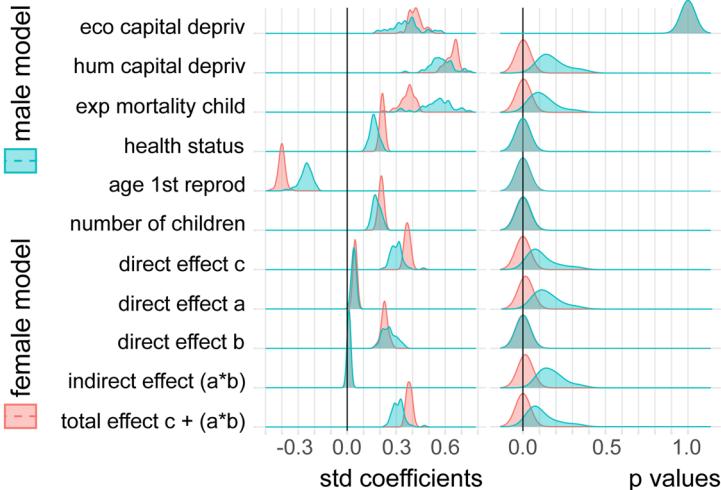
measurement of early life adversity is extremely challenging with our current conceptual models (Smith and Pollak, 2021). As a consequence, we only found weak support for our main hypothesis: only a small proportion of the positive association between adverse childhood conditions and the reproduction-maintenance trade-off is mediated by perceived control. Interestingly, a similar set of results emerged from the application of the same cross-validated SEMs to the independent data set of the European Social Study, with time orientation taken as the mediator of the association between early life adversity and the reproduction-maintenance trade-off. At least in the female sample, adverse childhood environments were weakly associated with a present-oriented worldview (a moderate negative effect of current income was however detected: median std.coeff = -0.18; median *p* < 0.001), which in turn was moderately associated with the reproduction-maintenance trade-off described above. However, the mediating effect of time orientation in the association between early life adversity and the reproduction-maintenance trade-off is again weak. In the male sample, these effects were simply absent.

Contrary to our initial hypotheses, these results suggest that early life adversity, perceived control and time orientation impact reproductive timing, fertility and health status in a relatively independent manner. This is mainly due to the fact that perceived control and time orientation are weakly associated with our early life adversity latent factor. A possible explanation of these weak associations is that the way perceived control and time

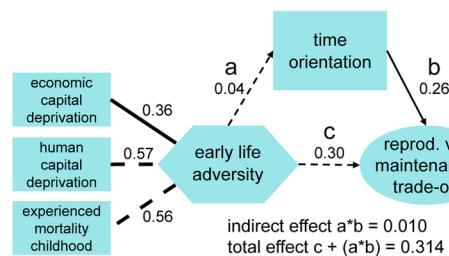
a. ESS models. Cross-validated fit indices



b. ESS models. std coeff and p values proba densities



c. ESS male model. Training data



d. ESS female model. Training data

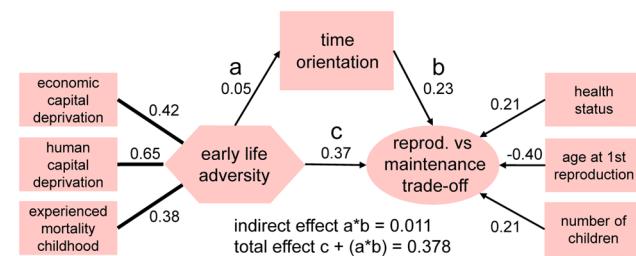


Fig. 2 ESS models. Main results. **a** Distributions of the goodness-of-fit indices of the male and female models cross-validated on the test datasets. Vertical lines indicate the median. **b** Distributions of the standardised coefficients and associated *p*-values of the indicators (see rectangles in panel **c**) estimated from fitting the model to the training datasets. The indirect effect represents the part of the effect of *Early life adversity* on the *Reproduction-maintenance trade-off* that is routed through *Time orientation*. **c, d** Structures and standardised parameters (median values) of the male (**c**) and female (**d**) models estimated from fitting the training datasets. Ellipses represent latent variables, rectangles represent their indicators, composite variables and direct measures. Significant paths are represented by bold lines and arrows.

orientation are measured here could be too simplistic to accurately represent such complex psychological constructs. For example, some authors (Shapiro et al., 1993) argue that perceived control (as well as time orientation, (Zimbardo and Boyd, 2015) might be better conceptualised as a combination of several dimensions such as locus of control (i.e., the degree to which individuals believe that they, as opposed to external factor such as chance or other agents, have control over their lives, Rotter, 1966; Lefcourt, 1976), self-efficacy (i.e., a person's ability to cope with a given situation based on the skills he or she possesses and the circumstances he or she faces, Bandura, 1977), learned helplessness (i.e., acceptance of powerlessness after repeated exposure to harsh events, Maier and Seligman, 1976), and desire of control. In other words, a more precise measure of perceived control and time orientation might have increased our chance of detecting an association between these constructs and early life adversity, an association often reported in the literature (Culpin et al., 2015; Di Pentima et al., 2019; Kraus et al., 2012; Pepper and Nettle, 2017). Nevertheless, this explanation is challenged by the robust associations we found between perceived control and time orientation with the reproduction-maintenance trade-off. An alternative explanation of the weak associations described above is that they represent the visible end of broader correlations encompassing higher levels of adversity than those found in the Western, industrialised, and affluent countries that comprise our two datasets. If this is true, running our models on more diverse samples could help validate our initial hypotheses.

Other interesting features of our results are worth discussing. First, while human and economic capital deprivation indicators were robustly associated with our latent composite adversity, experienced mortality was not (the only exception was with the ESS female model). Previous studies have shown mortality to be similarly associated with other adversity variables (Mell et al., 2018). This could be the result of relatively little variation in this measure in the industrialised and affluent European countries that constitute the EVS data set. Furthermore, our extrinsic mortality variable is indexed to the loss of the respondents' parents, which provides a very restricted view of what the true extrinsic mortality rate really is. Alternatively, there may be a meaningful dissociation between the economic and social variables on the one hand, and experienced mortality on the other. One important difference is that mortality is a more objective measure, whereas the other variables we used reflect more subjective judgments about relative deprivation. Interestingly, a recent study found that subjective indicators of SES were more strongly associated with a number of health and well-being outcomes than objective indicators (Rivenbark et al., 2020).

Second, we found important differences between the models fitted separately on male and female data. Overall, the model fit was better on the female data. This was notably caused by the fact that the number of children was significantly associated with the reproduction-maintenance trade-off only in the female model, hence making the factorial structure of this latent variable more robust than in the male model. One plausible explanation for this

difference is the fact that pregnancy itself is a reproductive trait that conveys direct maintenance costs for women (Jasienska et al., 2017). Indeed, the number of pregnancies (parity) has been found to be associated with markers of accelerated aging in women (Ryan et al., 2018). In addition, parity is robustly associated with increased risk of cardiovascular disease (Lawlor et al., 2003; Ness et al., 1993) and diabetes (Hinkula et al., 2006).

Third, we have uncovered some unexpected nonlinearities between the latent constructs. Specifically, the shape of the relationship between *Perceived control* with both *Early life adversity* and the *Reproduction-maintenance trade-off* followed a cubic pattern; whereas the shape of the relationship between *Time orientation* and both *Early life adversity* and the *Reproduction-maintenance trade-off* followed a quadratic pattern. These nonlinear patterns could result from some methodological artefacts, but they could also reveal a meaningful effect so far unaccounted for. Based on recent evidence of increased competences in individuals who have experienced more adversity (Frankenhuis and Nettle, 2020; Ellis et al., 2020), an intriguing possibility is that the nonlinear patterns we characterised above are, in these individuals, the outcomes of an increased sense of confidence in their own abilities. More specifically, some individuals who have experienced significant adversity might develop better abilities in certain cognitive and behavioural domains (e.g., threat detection, task set shifting). The increased sense of control and present orientation observed at the highest scores of early life adversity and reproduction-maintenance trade-off could then be the result of (accurate) perception of these increased abilities: individuals feel (and may in fact be) well equipped to deal with challenges found in adverse conditions and would therefore experience greater control over events that affect their lives. Alternatively, these observations could be simple methodological artefacts. For example, if respondents were unable to answer the perceived control or time orientation item questionnaire accurately (either because they did not understand the wording or because they were under high cognitive load and could not deliberate thoroughly), they might have responded with the maximum score. In this case, respondents with a perceived control score of 10 (or a time orientation of 0) would reflect both people who deliberately and accurately answered in this way and those who got it wrong, and whose actual scores would be distributed throughout the range of the variable.

Finally, our study also presents important limitations. Owing to the correlational nature of the EVS and ESS datasets, it is impossible to draw any conclusions about causality from our results. Individuals with a generally lower perceived control may be more likely to experience economic and social adversity, and people who favour reproductive goals over health goals may be more likely to have less control over their lives, rather than the other way around. However, this interpretation is unlikely to hold for several reasons. First, data were collected on adversity experienced during childhood, rather than currently. It is unlikely that the current perceived control retrospectively affects past experience, even though in the EVS and the ESS surveys, self-reported past experience may be corrupted by some sources of noise, such as social desirability effects or distorted memories. Moreover, a crucial assumption underlying our model is that *Perceived control* and *Time orientation* are relatively stable life traits. This is certainly not true, as multiple studies have shown within-individual variability in time in both of these constructs (Holman et al., 2016; Trommsdorff et al., 1979). It is very likely that this fact is partially responsible for the weak indirect effects. However, the mere existence of such variability does not entirely preclude the existence and the investigation of longer-term associations. For example, Kulas (1996) has measured Locus of control over a 3-year-period in an adolescent sample and

concluded that while some change in this trait was observable, it was rather stable in the observed period. This is even more remarkable as adolescence is thought to be a period of considerable developmental changes in various psychological traits. Similarly, while Holman et al. (2016) have found that 34–48% of the variance in Time perspective scales was due to changes within individuals across their observation period of 3 years, it might also be appreciated that the majority (52–66%) of the variance was due to inter-individual long-term differences. In conclusion, while certainly not unchanging, we believe that existing research indicate that both *Perceived control* and *Time orientation* are stable enough constructs, for our analyses to be meaningful (Holman et al., 2016; Kulas, 1996). Second, other studies with longitudinal designs have also provided support for time-dependent associations between early life adversity and the development of reproductive physiology (Amir et al., 2016). An additional caveat of our work is related to the fact that the EVS and ESS datasets are by definition restricted to European countries. Cross-cultural variability should not be underestimated when considering supposedly universal phenomena (Henrich et al., 2010). Our results therefore need to be replicated in a more diverse sample, which would include non-Western and non-industrialised societies. Note however that previous studies working with more culturally diverse groups of subjects have shown that environmental adversity (measured directly or indirectly) impacts cognition (e.g., intertemporal choice) and behaviour (social and academic behaviours) in relatively similar ways across these groups (Bulley and Pepper, 2017; Chang et al., 2019; Lee et al., 2018).

In conclusion, our study contributes to elucidating the complex effects of early life adversity on human psychology. Theory suggests that perceived control and time orientation may be two important psychological traits that mediate the effects of adversity in health and reproduction. Individuals may be less willing to invest in long-term strategies such as health maintenance when they believe that their lives, and the events that affect them, are not under their own control. Instead, they might invest in activities that offer more immediate fitness benefits, such as reproduction. We tested this hypothesis using a public survey data set and cross-validated structural equation models and found some support for it. Nevertheless, the small effect size indicates that much work remains to be done to fully characterise the relevant constructs and trade-offs.

Data availability

The EVS and WVS data used in the present study are respectively available at <http://www.worldvaluessurvey.org/WVSDocumentationWVL.jsp> and at <https://dbk.gesis.org/dbksearch/sdesc2.asp?no=4804&db=e&doi=10.4232/1.12253>. The imputed EVS and WVS data used in the present study, the R codes developed to extract and pre-process the data, to perform multiple imputations, to fit and cross-validate the models on the imputed data files are available at <https://osf.io/dh4jq/>.

Received: 16 July 2021; Accepted: 18 January 2022;

Published online: 14 February 2022

References

- Amir D, Jordan MR, Bribiescas RG (2016) A longitudinal assessment of associations between adolescent environment, adversity perception, and economic status on fertility and age of menarche. PLoS ONE 11(6):e0155883. <https://doi.org/10.1371/journal.pone.0155883>
- Arlot S, Celisse A (2010) A survey of cross-validation procedures for model selection. Stat Survey 4:40–79. <https://doi.org/10.1214/09-SS054>

Bandura A (1977) Self-efficacy: toward a unifying theory of behavioral change. *Psychol Rev* 84(2):191–215. <https://doi.org/10.1037/0033-295X.84.2.191>

Barger SD, Muldoon MF (2006) Hypertension labelling was associated with poorer self-rated health in the Third US National Health and Nutrition Examination Survey. *J Human Hypertens* 20(2):117–123. <https://doi.org/10.1038/sj.jhh.1001950>

Bar-Sadeh B, Rudnizky S, Pnueli L, Bentley GR, Stöger R, Kaplan A, Melamed P (2020) Unravelling the role of epigenetics in reproductive adaptations to early-life environment. *Nat Rev Endocrinol* 16(9):519–533. <https://doi.org/10.1038/s41574-020-0370-8>

Benyamin Y, Idler EL (1999) Community studies reporting association between self-rated health and mortality: additional studies, 1995 to 1998. *Res Aging* 21(3):392–401. <https://doi.org/10.1177/0164027599213002>

Breckler SJ (1990) Applications of covariance structure modeling in psychology: cause for concern? *Psychol Bull* 107(2):260–273

Brumbach BH, Figueiredo AJ, Ellis BJ (2009) Effects of harsh and unpredictable environments in adolescence on development of life history strategies: a longitudinal test of an evolutionary model. *Hum Nat* 20(1):25–51. <https://doi.org/10.1007/s12110-009-9059-3>

Bulley A, Pepper GV (2017) Cross-country relationships between life expectancy, intertemporal choice and age at first birth. *Evol Hum Behav* 38(5):652–658. <https://doi.org/10.1016/j.evolhumbehav.2017.05.002>

Cabeza de Baca T, Barnett MA, Ellis BJ (2016) The development of the child unpredictability schema: regulation through maternal life history trade-offs. *Evol Behav Sci* 10(1):43–55. <https://doi.org/10.1037/ebss0000056>

Cabeza de Baca T, Ellis BJ (2017) Early stress, parental motivation, and reproductive decision-making: applications of life history theory to parental behavior. *Curr Opin Psychol* 15:1–6. <https://doi.org/10.1016/j.copsyc.2017.02.005>

Chang L, Lu HJ, Lansford JE, Skinner AT, Bornstein MH, Steinberg L, Dodge KA, Chen BB, Tian Q, Bacchini D, Deater-Deckard K, Pastorelli C, Alampay LP, Sorbring E, Al-Hassan SM, Oburu P, Malone PS, Di Giunta L, Tirado LMU, Tapanya S (2019) Environmental harshness and unpredictability, life history, and social and academic behavior of adolescents in nine countries. *Dev Psychol* 55(4):890–903. <https://doi.org/10.1037/dev0000655>

Culpin I, Stapinski L, Miles ÖB, Araya R, Joinson C (2015) Exposure to socio-economic adversity in early life and risk of depression at 18 years: The mediating role of locus of control. *J Affect Disord* 183:269–278. <https://doi.org/10.1016/j.jad.2015.05.030>

Del Giudice M, Gangestad SW, Kaplan HS (2015) Life History Theory and Evolutionary Psychology. In: Buss DM (ed.), *The Handbook of Evolutionary Psychology*: Vol. 1: Foundations (2nd edn.). Wiley. pp. 88–114

Di Pentima L, Toni A, Schneider BH, Tomás JM, Oliver A, Attili G (2019) Locus of control as a mediator of the association between attachment and children's mental health. *J Genet Psychol* 180(6):251–265. <https://doi.org/10.1080/00221325.2019.1652557>

Ellis BJ, Abrams LS, Masten AS, Sternberg RJ, Tottenham N, Frankenhuus WE (2020) Hidden talents in harsh environments. *Dev Psychopathol* 1–19. <https://doi.org/10.1017/S0954579420000887>

Ellis BJ, Del Giudice M (2019) Developmental adaptation to stress: an evolutionary perspective. *Ann Rev Psychol* 70(1):111–139. <https://doi.org/10.1146/annurev-psych-122216-011732>

Enders C, Bandalo D (2001) The relative performance of full information maximum likelihood estimation for missing data in structural equation models. *Struct Equ Modeling: Multidiscip J* 8(3):430–457. https://doi.org/10.1207/S15328007SEM0803_5

Frankenhuus WE, Nettle D (2020) The strengths of people in poverty. *Curr Direct Psychol Sci* 29(1):16–21. <https://doi.org/10.1177/0963721419881154>

Goldberg P, Guégan A, Schmaus A, Nakache J-P, Goldberg M (2001) Longitudinal study of associations between perceived health status and self reported diseases in the French Gazel cohort. *J Epidemiol Commun Health* 55(4):233–238. <https://doi.org/10.1136/jech.55.4.233>

Grace JB, Bollen KA (2008) Representing general theoretical concepts in structural equation models: the role of composite variables. *Environ Ecol Stat* 15(2):191–213. <https://doi.org/10.1007/s10651-007-0047-7>

Haring R, Feng Y-S, Moock J, Völzke H, Dörr M, Nauck M, Wallaschofski H, Kohlmann T (2011) Self-perceived quality of life predicts mortality risk better than a multi-biomarker panel, but the combination of both does best. *BMC Med Res Methodol* 11(1):103. <https://doi.org/10.1186/1471-2288-11-103>

Henrich J, Heine SJ, Norenzayan A (2010) The weirdest people in the world? *Behav Brain Sci* 33(2–3):61–83. <https://doi.org/10.1017/S0140525X0999152X>

Hill EM, Jenkins J, Farmer L (2008) Family unpredictability, future discounting, and risk taking. *J Socio-Econ* 37(4):1381–1396. <https://doi.org/10.1016/j.socrec.2006.12.081>

Hill K, Kaplan H (1999) Life history traits in humans: theory and empirical studies. *Ann Rev Anthropol* 28(1):397–430. <https://doi.org/10.1146/annurev.anthro.28.1.397>

Hinkula M, Kauppila A, Näyhä S, Pukkala E (2006) Cause-specific mortality of grand multiparous women in Finland. *Am J Epidemiol* 163(4):367–373. <https://doi.org/10.1093/aje/kwj048>

Holman EA, Silver RC, Mogle JA, Scott SB (2016) Adversity, time, and well-being: a longitudinal analysis of time perspective in adulthood. *Psychol Aging* 31(6):640–651. <https://doi.org/10.1037/pag0000115>

Hu L, Bentler PM (1999) Cutoff criteria for fit indexes in covariance structure analysis: conventional criteria versus new alternatives. *Struct Equ Modeling* 6(1):1–55. <https://doi.org/10.1080/10705519909540118>

Hughes K, Bellis MA, Hardcastle KA, Sethi D, Butchart A, Mikton C, Jones L, Dunne MP (2017) The effect of multiple adverse childhood experiences on health: a systematic review and meta-analysis. *Lancet Public Health* 2(8):e356–e366. [https://doi.org/10.1016/S2468-2667\(17\)30118-4](https://doi.org/10.1016/S2468-2667(17)30118-4)

Idler EL, Benyamin Y (1997) Self-rated health and mortality: a review of twenty-seven community studies. *J Health Soc Behav* 38(1):21. <https://doi.org/10.2307/2955359>

Jasienska G, Bribiescas RG, Furberg A-S, Helle S, Núñez-de la Mora A (2017) Human reproduction and health: an evolutionary perspective. *The Lancet* 390(10093):510–520. [https://doi.org/10.1016/S0140-6736\(17\)30573-1](https://doi.org/10.1016/S0140-6736(17)30573-1)

Johnson DR, Creech JC (1983) Ordinal measures in multiple indicator models: a simulation study of categorization error. *Am Sociol Rev* 48(3):398. <https://doi.org/10.2307/2095231>

Jorgensen TD, Pornprasertmanit S, Schoemann AM, Rosseel Y (2020) *SemTools: Useful tools for structural equation modeling*. R package version 0.5-3. <https://CRAN.R-project.org/package=semTools>

Jylhä M, Volpato S, Guralnik JM (2006) Self-rated health showed a graded association with frequently used biomarkers in a large population sample. *J Clin Epidemiol* 59(5):465–471. <https://doi.org/10.1016/j.jclinepi.2005.12.004>

Kline RB (2015) *Principles and Practice of Structural Equation Modeling* (4th edn.). Guilford Press

Kraus MW, Piff PK, Mendoza-Denton R, Rheinschmidt ML, Keltner D (2012) Social class, solipsism, and contextualism: How the rich are different from the poor. *Psychol Rev* 119(3):546–572. <https://doi.org/10.1037/a0028756>

Kulas H (1996) Locus of control in adolescence: a longitudinal study. *Adolescence* 31(123):721–729

Kuzawa CW, Chugani HT, Grossman LI, Lipovich L, Muzik O, Hof PR, Wildman DE, Sherwood CC, Leonard WR, Lange N (2014) Metabolic costs and evolutionary implications of human brain development. *Proc Natl Acad Sci USA* 111(36):13010–13015. <https://doi.org/10.1073/pnas.1323099111>

Lawlor DA, Emberson JR, Ebrahim S, Whincup PH, Wannamethee SG, Walker M, Smith GD (2003) Is the association between parity and coronary heart disease due to biological effects of pregnancy or adverse lifestyle risk factors associated with child-rearing?: Findings From the British Women's Heart and Health Study and the British Regional Heart Study. *Circulation* 107(9):1260–1264. <https://doi.org/10.1161/01.CIR.0000053441.43495.1A>

Lee AJ, DeBruine LM, Jones BC (2018) Individual-specific mortality is associated with how individuals evaluate future discounting decisions. *Proc R Soc B: Biol Sci* 285 (20180304). <https://doi.org/10.1098/rspb.2018.0304>

Lefcourt HM (1976) Locus of control and the response to aversive events. *Can Psychol Rev* 17(3):202–209. <https://doi.org/10.1037/h0081839>

Legleye S, Janssen E, Beck F, Chau N, Khlat M (2011) Social gradient in initiation and transition to daily use of tobacco and cannabis during adolescence: a retrospective cohort study: Tobacco and cannabis use during adolescence. *Addiction* 106(8):1520–1531. <https://doi.org/10.1111/j.1360-0443.2011.03447.x>

Maier SF, Seligman MEP (1976) Learned helplessness: theory and evidence. *J Exp Psychol: Gen* 105(1):3–46. <https://doi.org/10.1037/0096-3445.105.1.3>

McDade TW (2005) Life history, maintenance, and the early origins of immune function. *Am J Hum Biol* 17(1):81–94. <https://doi.org/10.1002/ajhb.20095>

McDade TW, Georgiev AV, Kuzawa CW (2016) Trade-offs between acquired and innate immune defenses in humans. *Evol Med Public Health* (1):1–16. <https://doi.org/10.1093/emph/eov033>

Mell H, Baumard N, André JB (2021) Time is money. Waiting costs explain why selection favors steeper time discounting in deprived environments. *Evol Human Behav* S1090513821000143. <https://doi.org/10.1016/j.evolhumbehav.2021.02.003>

Mell H, Safra L, Algan Y, Baumard N, Chevallier C (2018) Childhood environmental harshness predicts coordinated health and reproductive strategies: a cross-sectional study of a nationally representative sample from France. *Evol Hum Behav* 39(1):1–8. <https://doi.org/10.1016/j.evolhumbehav.2017.08.006>

Melotti R, Heron J, Hickman M, Macleod J, Araya R, Lewis G (2011) Adolescent alcohol and tobacco use and early socioeconomic position: The ALSPAC Birth Cohort. *Pediatrics* 127(4):e948–e955. <https://doi.org/10.1542/peds.2009-3450>

Miller GE, Chen E, Parker KJ (2011) Psychological stress in childhood and susceptibility to the chronic diseases of aging: Moving toward a model of behavioral and biological mechanisms. *Psychol Bull* 137(6):959–997. <https://doi.org/10.1037/a0024768>

Nandi A, Glymour MM, Subramanian SV (2014) Association among socioeconomic status, health behaviors, and all-cause mortality in the United States. *Epidemiology* 25(2):170–177. <https://doi.org/10.1097/EDE.0000000000000038>

Ness RB, Harris T, Cobb J, Flegal KM, Kelsey JL, Balanger A, Stunkard AJ, D'Agostino RB (1993) Number of pregnancies and the subsequent risk of cardiovascular disease. *New Engl J Med* 328(21):1528–1533

Nettle D (2010) Dying young and living fast: Variation in life history across English neighborhoods. *Behav Ecol* 21(2):387–395. <https://doi.org/10.1093/beheco/arp202>

Nettle D (2011) Flexibility in reproductive timing in human females: Integrating ultimate and proximate explanations. *Philos Trans R Soc B: Biol Sci* 366(1563):357–365. <https://doi.org/10.1098/rstb.2010.0073>

Nettle D, Coall DA, Dickins TE (2011) Early-life conditions and age at first pregnancy in British women. *Proc R Soc B: Biol Sci* 278(1712):1721–1727. <https://doi.org/10.1098/rspb.2010.1726>

Nettle D, Frankenhuys WE (2019) The evolution of life-history theory: A bibliometric analysis of an interdisciplinary research area. *Proc R Soc B: Biol Sci* 286(1899):20190040. <https://doi.org/10.1098/rspb.2019.0040>

Norman G (2010) Likert scales, levels of measurement and the “laws” of statistics. *Adv Health Sci Educ* 15(5):625–632. <https://doi.org/10.1007/s10459-010-9222-y>

Oberski D (2014). lavaan.survey: an R package for complex survey analysis of structural equation models. *J Stat Softw*, 57(1). <https://doi.org/10.18637/jss.v057.i01>

Pepper GV, Nettle D (2014) Perceived extrinsic mortality risk and reported effort in looking after health: testing a behavioral ecological prediction. *Hum Nat* 25(3):378–392. <https://doi.org/10.1007/s12110-014-9204-5>

Pepper GV, Nettle D (2017) The behavioural constellation of deprivation: causes and consequences. *Behav Brain Sci* 40:e314. <https://doi.org/10.1017/S0140525X1600234X>

Piketty T, Saez E (2014) Inequality in the long run. *Science* 344(6186):838–843. <https://doi.org/10.1126/science.1251936>

Preacher KJ (2006) Quantifying parsimony in structural equation modeling. *Multivar Behav Res* 41(3):227–259. https://doi.org/10.1207/s15327906mbr4103_1

Rivenbark J, Arseneault L, Caspi A, Danese A, Fisher HL, Moffitt TE, Rasmussen LH, Russell MA, Odgers CL (2020) Adolescents' perceptions of family social status correlate with health and life chances: a twin difference longitudinal cohort study. *Proc Natl Acad Sci USA*, 201820845. <https://doi.org/10.1073/pnas.1820845116>

Roberts S, Pashler H (2000) How persuasive is a good fit? A comment on theory testing. *Psychol Rev* 107(2):358–367

Ross LT, Hill EM (2002) Childhood unpredictability, schemas for unpredictability, and risk taking. *Soc Behav Pers: Int J* 30(5):453–473. <https://doi.org/10.2224/sbp.2002.30.5.453>

Rosseel Y (2012). lavaan: an R package for structural equation modeling. *J Stat Softw*, 48(2). <https://doi.org/10.18637/jss.v048.i02>

Rotter JB (1966) Generalized expectancies for internal versus external control of reinforcement. *Psychol Monogr: Gen Appl* 80(1):1–28. <https://doi.org/10.1037/h0092976>

Ryan CP, Hayes MG, Lee NR, McDade TW, Jones MJ, Kobor MS, Kuzawa CW, Eisenberg DTA (2018) Reproduction predicts shorter telomeres and epigenetic age acceleration among young adult women. *Sci Rep* 8(1):11100. <https://doi.org/10.1038/s41598-018-29486-4>

Satorra A, Bentler PM (2001) A scaled difference chi-square test statistic for moment structure analysis. *Psychometrika* 66(4):507–514

Sear R (2020) Do human 'life history strategies' exist? *Evol Hum Behav* 41(6):513–526. <https://doi.org/10.1016/j.evolhumbehav.2020.09.004>

Shapiro DH, Blinder BJ, Hagman J, Pituck S (1993) A psychological "sense-of-control" profile of patients with anorexia nervosa and bulimia nervosa. *Psychol Rep* 73(2):531–541. <https://doi.org/10.2466/pr0.1993.73.2.531>

Smith KE, Pollak SD (2021) Rethinking concepts and categories for understanding the neurodevelopmental effects of childhood adversity. *Perspect Psychol Sci* 16(1):67–93. <https://doi.org/10.1177/1745691620920725>

Stevens JR, Stephens DW (2010) The adaptive nature of impulsivity. In: Madden GJ & Bickel WK (eds.) *Impulsivity: the behavioral and neurological science of discounting*. (pp. 361–387). Am Psychol Assoc. <https://doi.org/10.1037/12069-013>

Trommsdorff G, Lamm H, Schmidt RW (1979) A longitudinal study of adolescents' future orientation (time perspective). *J Youth Adolesc* 8(2):131–147. <https://doi.org/10.1007/BF02087616>

van Buuren S, Groothuis-Oudshoorn K (2011) mice: multivariate imputation by chained equations in R. *J Stat Softw*, 45(3). <https://doi.org/10.18637/jss.v045.i03>

Zimbardo PG, Boyd JN (2015). Putting time in perspective: a valid, reliable individual-differences metric. In: Stolarski M, Fieulaine N, van Beek W (eds.) *Time perspective theory: review, research and application*. Springer International Publishing, pp. 17–55

Zucman G (2019) Global wealth inequality. *Ann Rev Econ* 11:109–138

Pinheiro J, Bates D, DebRoy S, Sarkar D, R Core Team (2022). nlme: Linear and Nonlinear Mixed Effects Models. R package version 3.1-155. <https://CRAN.R-project.org/package=nlme>

Acknowledgements

This work was supported by the FrontCog funding under grant number ANR-17-EURE-0017. POJ was supported by ANR-10-LABX-0087 IEC and ANR-10-IDEX-0001-02 PSL*. VC was supported by the Agence Nationale de la Recherche grants ANR-16-CE37-0012-01 (ANR JCJC) and ANR-19-CE37-0014-01 (ANR PRC).

Competing interests

The author(s) declare no competing interests.

Ethical approval

The European Values Study (EVS) and the European Social Survey (ESS) are large-scale, cross-national, and longitudinal survey research programmes on basic human values. The EVS is managed by the Council of Programme Directors, who discuss the general outlines of the project and approve the final questionnaire and the survey method. The ESS ERIC is governed by a General Assembly, represented by National Representatives, which has three standing committees: a Scientific Advisory Board, a Methods Advisory Board and a Finance Committee. The ESS ERIC subscribes to the Declaration on Professional Ethics of the International Statistical Institute.

Informed consent

As only open source data were used, this article does not contain any studies with human participants performed by any of the authors. All the necessary information about the respondents' informed consent, data privacy policies and storage is available at <https://www.ssoar.info/ssoar/handle/document/70110> for the EVS, and at https://www.europeansocialsurvey.org/about/web_privacy.html for the ESS.

Additional information

Supplementary information The online version contains supplementary material available at <https://doi.org/10.1057/s41599-022-01066-y>.

Correspondence and requests for materials should be addressed to Bence Csaba Farkas.

Reprints and permission information is available at <http://www.nature.com/reprints>

Publisher's note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.



Open Access This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons license, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons license, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons license and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this license, visit <http://creativecommons.org/licenses/by/4.0/>.

© The Author(s) 2022