

Outcome context-dependence is not WEIRD: Comparing reinforcement- and description-based economic preferences worldwide

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43 **Abstract (144/150)**

44

45 Recent evidence indicates that reward value encoding in humans is highly context-dependent,
46 leading to suboptimal decisions in some cases. But whether this computational constraint on
47 valuation is a shared feature of human cognition remains unknown. To address this question, we
48 studied the behavior of individuals from across 11 countries of markedly different socioeconomic
49 and cultural makeup using an experimental approach that reliably captures context effects in
50 reinforcement learning. Our findings show that all samples presented evidence of similar
51 sensitivity to context. Crucially, suboptimal decisions generated by context manipulation were
52 not explained by risk aversion, as estimated through a separate description-based choice task
53 (i.e., lotteries) consisting of matched decision offers. Conversely, risk aversion significantly
54 differed across countries. Overall, our findings suggest that context-dependent reward value
55 encoding is a hardcoded feature of human cognition, while description-based decision-making is
56 significantly sensitive to cultural factors.

57

58

59 Introduction (917/750-1000)

60

61 Cross-cultural differences in economic decision-making processes have been investigated in
62 several domains, such as risk preference and behavioural game theory. Although several
63 qualitative features seem to be preserved (such as prospect theory-like preferences and delay
64 discounting^{1,2}), evidence has repeatedly shown culturally-driven differences in many decision-
65 making traits^{3,4,5}.

66

67 To date, efforts to assess the cross-cultural stability of decision-making processes have mainly (if
68 not only) focused on what can be defined as “description-based” paradigms, i.e., using tasks
69 where all the decision-relevant information such as prospective outcomes and their “costs” can
70 be inferred from explicit cues or instructions^{6,7,8}.

71

72 However, little is known concerning the cross-cultural stability (or the lack thereof) of experience-
73 based decisions, which encompass all situations where the decision-making variables have to be
74 inferred from past experience^{9,10}. One prominent conceptual framework to investigate
75 experience-based decision processes is reinforcement learning (RL), whose empirical and
76 experimental foundations span multiple disciplines from neuroscience to artificial intelligence¹¹.

77

78 The lack of cross-cultural investigation of human RL processes is particularly problematic, given
79 that RL is a pervasive cognitive process, with many important implications for mental health,
80 education and economics^{12,13,14,15}. Despite its general adaptive value (seek rewards and avoid
81 punishments) laboratory-based research has illustrated that RL processes in many circumstances
82 deviate from a statistical and normative standpoints^{16,17}. Determining whether such RL
83 reinforcement learning biases are cultural artefacts, or rather stable components of human
84 decision processes, can provide additional fundamental hints to understand the computational
85 constraints of bounded rationality^{18,19}.

86

87 Among several features characterizing human RL, the notion of outcome (or reward) context-
88 dependence has recently risen to prominence¹⁶. More specifically, a series of studies conducted
89 mostly with Western, Educated, Industrialized and Democratic (WEIRD) populations²⁰ have
90 shown that in many RL tasks, participants encode outcomes (i.e., rewards and punishments) in a
91 context-dependent manner^{21,22,23,24}. While there may not be a consensus yet concerning the
92 exact functional form of such context-dependency, the available findings overwhelmingly favour
93 the idea that subjective outcomes are calculated relatively, following some form of range
94 normalization^{25,26,27}. Such context-dependence-induced rescaling of subjective outcomes is often
95 interpreted as a consequence of efficient information coding in the human brain^{28,29}. According
96 to this hypothesis, this feature can be understood as the result of fundamental

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97 neurocomputational constraints akin to those observable in perceptual decision-making^{30,31,32}. In
98 accordance with this proposal of outcome context-dependence in RL as a form of efficient coding,
99 multiple studies using similar tasks in different species have consistently found evidence of range-
100 value adaptation, which suggests that this may be an evolutionary stable, “hard coded”, principle
101 of brain functioning^{37,38}.

102

103 One well-known consequence of context-dependence in RL is that, in some cases, it can induce
104 suboptimal decisions^{25,26,27}. In particular learning contexts, individuals mistakenly attribute
105 higher subjective values to objectively worse options because of how these options are appraised
106 in relation to the local reward distribution, resulting in choices that fail to maximize reward. If
107 indeed there exists such a fundamental computational constraint in the human brain, the
108 behavioural signatures of context-dependence should be a stable feature of decision-making,
109 and thus persist across different populations and cultures. In the present work, we set out to test
110 this hypothesis by leveraging a task capable of eliciting context-dependent RL behaviours, and
111 deploying it across eleven countries of remarkably different socio-economic and cultural makeup
112 (Argentina, Iran, Russia, Japan, China, India, Israel, Chile, Morocco, France and the United States).
113 This allowed us to test the cross-cultural stability of context-dependent value encoding in human
114 RL, and thus assess for the first time its putative role as a core computational process of
115 experience-based decision-making.

116

117 In addition, we also administered to our participants a description-based decision-making task
118 that included the same decision contexts as the RL task. The rationale behind this second task
119 was two-fold. First, it allowed us to determine to which extent choice behavior measured in the
120 RL task can be explained by risk aversion, using standard procedures in behavioural economics.
121 Second, it gave us the opportunity to compare for the first time the variability of experience-
122 based and description-based decision-making processes across countries.

123

124 Our results indicate a remarkable similarity in how context effects manifest in decisions from
125 experience and suboptimal choice across countries, consistent with the idea that outcome
126 representation in human RL behaviours may reflect conserved constraints on cognition. Our
127 results also showed that risk aversion inferred from the description-based lottery task could not
128 account for these effects. Interestingly, description-based decisions were also found to be highly
129 variable across countries, further confirming the functional dissociation between the behaviour
130 elicited by the two modalities^{6,7,33}. Exploratory analyses using independent socio-economic,
131 cultural and cognitive measures taken from our samples further showed that the origin of cross-
132 country differences in description-based decisions is multifactorial, as previously found for risk
133 and other cognitive domains^{5,34,35}. Overall, our results suggest that reinforcement (experience-
134 based) decision processes are much more culturally stable than description-based ones and have

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135 important implications for theories of bounded rationality^{18,19}. We conclude this work by
136 discussing the possible implications of these results for the current implementation of policies
137 and interventions aimed at contrasting the burden of biased decision-making.

138

139

140 **Results**

141

142 **Behavioural protocol**

143 Our behavioural protocol consisted of a reinforcement learning (RL; i.e. experience-based) task,
144 in the form of a previously validated two-armed bandit task²⁶, followed by a description-based
145 decision-making task consisting of choices between lotteries (**Fig. 1A**). Both decision-making
146 tasks were preceded by dedicated instructions and a short training session, and succeeded by a
147 series of questionnaires directed at obtaining information on participants' socioeconomic,
148 cultural, and cognitive features, as well as general demographics (**Supplementary Materials - Fig**
149 **S1**). The RL task consisted of two phases: a Learning phase and a Transfer phase. Its design and
150 implementation reproduced that of Bavard et al., 2021²⁶. During the Learning phase, participants
151 were presented with eight abstract icon cues, each representing a lottery of non-disclosed
152 expected value, paired in four stable decision contexts. In the Learning phase, each decision
153 context featured only two possible outcomes: either 10/0 points or 1/0 points. The outcomes
154 were probabilistic (75% or 25%). For convenience, contexts were labelled by taking into account
155 the difference in expected value between the most and the least rewarding option, i.e. the
156 expected value-maximizing ("correct") and the expected value-minimizing ("wrong") options
157 (**Fig. 1B**). In the ensuing Transfer phase, these same eight lotteries were rearranged into new
158 decision contexts [as previously done in similar designs for humans and birds^{22,26,36,37,38}]. In
159 addition to the change in decision contexts, the key difference between the Learning and the
160 Transfer phases was that, while during the former participants were presented with complete
161 feedback, in the latter no feedback was provided, so that choices could only be based on values
162 learned during the Learning phase (**Fig. 1B**). Finally, we conducted an additional task, which we
163 identified as the Lottery task (**Fig. 1C**). There, the values (magnitudes and probabilities) of the
164 options were explicitly disclosed. The Lottery task featured the same decision contexts used in
165 the Transfer phase, and four additional contexts designed to better assess risk preferences. These
166 last contexts consisted of choices comparing varying probabilities of winning 10 points (100%,
167 75%, 50%, 25%) against the certainty of winning 1 point.

168

169 **Population Demographics**

170 Our main goal was to test the replicability of context-dependence in RL across countries (while
171 disentangling it from risk aversion as standardly assessed in economic value-based decision-
172 making tasks). Thus, our final sample included 11 countries (USA, Israel, Japan, France, Chile,
173 Argentina, Russia, Iran, China, Morocco, India), covering a total of 5 continents and 10 languages
174 (**Fig. 1D**). Country selection was aimed at portraying a gradual spread across the United Nations'
175 Human Development Index³⁹. This coefficient is built with many metrics, such as GDP,
176 industrialization, mean education level, income inequality, and liberty indexes (**Fig. 1E, left**). To
177 assess the cultural spread of the selected countries, we used the 1981-2014 dataset of

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178 Muthukrishna and colleagues' cultural distance metric⁴⁰, to estimate the cultural difference
179 between each of the selected countries with respect to the USA and India, which represented
180 the higher and lower HDI values in our sample (**Fig. 1E, right**).

181 In order to ensure that our samples would adequately represent the culture of the country to
182 which they belonged, inclusion criteria required that participants: (1) had the target country
183 nationality, (2) resided in the target country, (3) had completed at least the full basic education
184 cycle in the target country, and (4) spoke the country's official language as their native language.
185 These criteria were assessed for each participant during a video meeting prior to launching the
186 experiment. The meeting, task instructions, and questionnaires were delivered in each country's
187 official language, by local researchers.

188 Additionally, to confirm the diversity of the sample beyond country macrometrics, participants
189 completed individual questionnaires on socioeconomic status⁴¹, individualistic/collectivistic
190 tendencies⁴², centrality of religiosity in their social environment⁴³, and a cognitive reflection
191 test⁴⁴ (see **Methods** for a detailed description of each metric).

192 Sample sizes for each country were set based on a power analysis conducted based on the online
193 results of Bavard et al., 2021²⁶ (n = 46 per country, see **Methods**). After exclusions (failure to
194 complete the task n = 43; troubleshooting/translation issues during task rollout n = 19), a
195 remainder of n = 561 participants (342 female; mean age(SD) = 24.4(4.6)) composed the final
196 sample (n = 51 on average per country). Separate linear regressions, using each of the
197 demographic and sociocultural indexes as predictors of nationality, confirmed that country
198 samples were significantly different in many respects. A summary of these differences,
199 demographic information, sample sizes and exclusions can be found in **Table 1**. Detailed results
200 of the regressions can be found in the Supplementary Materials (**Table S1**).

201

202 **Reinforcement learning task (experience-based)**

203 We first looked at performance in both RL phases. We focused on correct responses (i.e.,
204 probability of picking the expected value-maximizing choice) as the behavioural dependent
205 variable. Correct response rate was analysed separately in each RL phase (i.e. Learning and
206 Transfer), as a function of decision context (within-subjects variable) and country (between-
207 subjects variable). We also compared the correct response rate against chance level (0.5) to
208 assess learning and preferences. As in previous studies using the same or similar designs^{22,26}, of
209 particular relevance for the demonstration of outcome context-dependence were: i) the
210 comparison of accuracies between the $\Delta EV = 5.0$ and the $\Delta EV = 0.5$ decision contexts in the
211 Learning phase (where absence of difference – magnitude effect - is taken as a sign of relative
212 value learning) and ii) the preference expressed in the $\Delta EV = 1.75$ decision context of the Transfer
213 test (where below-chance accuracy is taken as an indicator of context-dependent value
214 rescaling).

215 Results showed that the average correct response rate for the Learning phase was significantly

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216 different from chance level 0.5 for all countries and decision contexts (**Fig. 2A**), which confirmed
217 that learning had occurred (pooled sample: $\Delta EV = 5$, 0.8 ± 0.2 , $t(560) = 42$, $p < .0001$, $d(95\% CI) =$
218 $1.8(1.66, 1.92)$; $\Delta EV = 0.5$, 0.8 ± 0.2 , $t(560) = 38$, $p < .0001$, $d = 1.6(1.49, 1.74)$; see **Supplementary**
219 **Materials - Table S3** for model selection, **Table S4** for full regression results). While we found
220 significant differences in aggregate performance between countries (Country main effect: $\chi^2 =$
221 58 , $DF = 10$, $p = <.0001$), learning and above-chance performance levels were observable in all
222 samples and contexts (**Fig. S2**).

223 Importantly, we did not find evidence for any magnitude effects in any of the country samples,
224 meaning that the learning performance was the same in the $\Delta EV = 5$ and the $\Delta EV = 0.5$ in all
225 countries (Decision context main effect: $\chi^2 = 2$, $DF = 1$, $p = 0.14$; Decision context x Country
226 interaction: $\chi^2 = 12$, $DF = 10$, $p = 0.29$). Further AICc weight ratio analysis confirmed a lack of
227 magnitude effect (i.e., a model including Decision Context as a regressor was 0.01 times as likely
228 to predict accuracy as the same model without it).

229 We then turned to the analysis of the Transfer phase (**Fig. 2B**). In this case, correct choice rates
230 were strongly modulated across decision contexts (Decision Context main effect: $\chi^2 = 326$, $DF =$
231 3 , $p = <.0001$). Here, we did not find evidence for any country effects (Country main effect: $\chi^2 =$
232 18 , $DF = 10$, $p = 0.05$; Decision context x Country interaction: $\chi^2 = 41$, $DF = 30$, $p = 0.09$). Further
233 AICc weight ratio analysis indicated a lack of Country effect (i.e. a model including Country as a
234 regressor was 0 times as likely to predict accuracy as the same model without it).

235 Replicating previous findings, and indicating that participants could successfully retrieve and
236 generalize the values learned during the Learning phase, correct choice rates in the $\Delta EV = 7.25$
237 and the $\Delta EV = 6.75$ decision contexts were well above chance level (0.7 ± 0.3 , $t(560) = 15$, $p <$
238 $.0001$, $d = 0.6(0.55, 0.73)$; $\Delta EV = 6.75$, 0.56 ± 0.4 , $t(560) = 3.5$, $p < .001$, $d = 0.15(0.07, 0.23)$).
239 Crucially, however, accuracy in the $\Delta EV = 1.75$ context was below chance level for all countries,
240 indicative of context-dependence induced suboptimal preferences (pooled sample: 0.33 ± 0.3 ,
241 $t(560) = -12$, $p < .0001$, $d = -0.5(-0.6, -0.4)$; see individual per-country T-tests in **Supplementary**
242 **Materials - Table S5**). Once again, while significant differences in aggregate performance
243 between samples were found (Country main effect: $\chi^2 = 19$, $DF = 10$, $p = .04$), the evidence did
244 not indicate any interaction between country and decision contexts (Country x Decision context
245 interaction: $\chi^2 = 40$, $DF = 30$, $p = 0.1$). Crucially, the presence of suboptimal behaviour in the ΔEV
246 $= 1.75$ context was observable in every country (see **Supplementary Materials - Table S5**), with
247 no significant differences between countries (**Fig 2.E, left**; see **Supplementary Materials - Table**
248 **S6** for post-hoc pairwise contrasts).

249
250 These results replicated previous findings^{22,26}, and showed that the behavioural signatures of
251 outcome context-dependence were cross-culturally stable in the RL task. Contrary to what a
252 model encoding values on an absolute scale would have predicted, performance was not affected
253 by the outcome magnitude during the Learning phase: this constitutes a positive manifestation

254 of context-dependent adaptive coding²⁸. Additionally, preferences were globally below chance
 255 in the $\Delta EV = 1.75$ condition. Namely, a previously optimal option ($EV = 0.75$) was preferred to a
 256 previously suboptimal option ($EV = 2.5$) despite its expected value being higher in the new
 257 decision context. This illustrated the already-known negative side of outcome context
 258 dependence in the context of RL: suboptimal decisions may arise when options are extrapolated
 259 from their original context.

260

261 **Lottery task (description-based)**

262 We then analysed participants' preferences in the description-based Lottery task (**Figs. 2C, 2D**).
 263 We first considered choices in the decision problems aimed at benchmarking risk preferences,
 264 where a sure small payoff (1pt) was presented against risky options with varying probabilities of
 265 delivering a bigger payoff (10pts). These four decision problems allowed us to estimate risk
 266 preference, quantified as the decrease in expected value-maximizing choice rates as the
 267 probability for obtaining the larger payoff decreased (i.e. propensity to choose the objectively
 268 higher value option as the levels of risk for that option increased). Results showed a coherent
 269 modulation of decision context on choice behaviour: as the risk involved increased, choice ratios
 270 for the objectively higher value offers decreased for all countries (pooled sample: $\Delta EV = 9$, 0.94
 271 ± 0.1 , $t(560) = 60$, $p < .0001$, $d = 2.6$; $\Delta EV = 6.5$, 0.79 ± 0.2 , $t(560) = 23$, $p < .0001$, $d = 1$; $\Delta EV = 4$,
 272 0.72 ± 0.3 , $t(560) = 16$, $p < .0001$, $d = 1$; $\Delta EV = 1.5$, 0.53 ± 0.4 , $t(560) = 2$, $p = 0.09$, $d = 0$; Decision
 273 Context main effect: $\chi^2 = 326$, $DF = 3$, $p = <.0001$; see **Supplementary Materials - Table S3** for
 274 model selection, **Table S4** for full regression results). Interestingly, while risk affected
 275 performance for all country samples, it did so differently across countries (Country main effect:
 276 $\chi^2 = 57$, $DF = 10$, $p = <.0001$; Country x Decision Context interaction: $\chi^2 = 100$, $DF = 30$, $p = <.0001$;
 277 see **Supplementary Materials - Table S5** for per-country T-test analyses). This indicated that
 278 preferences expressed in the description-based task were not cross-culturally stable, unlike
 279 behaviour observed in the RL task.

280 After assessing the detectability of risk aversion in the benchmark decision contexts of the Lottery
 281 task, we analysed preferences in the decision contexts homologous to those of the Transfer
 282 phase in RL (**Fig. 2D**). This allowed us to directly compare between experience-based and
 283 description-based preferences. We focused mainly on the behaviour expressed at the $\Delta EV = 1.75$
 284 decision context, where a tendency to significantly choose suboptimal choices can be interpreted
 285 as a sign of context dependence in the RL task. Crucially, and contrary to RL behavior, results
 286 showed that in all countries correct choice rate was significantly above chance for this decision
 287 problem in the description-based task (pooled sample: $\Delta EV = 7.25$, 0.9 ± 0.1 , $t(560) = 58$, $p <$
 288 $.0001$, $d = 2.4$; $\Delta EV = 6.75$, 0.9 ± 0.1 , $t(560) = 51$, $p < .0001$, $d = 2$; $\Delta EV = 2.25$, 0.9 ± 0.1 , $t(560) =$
 289 47 , $p < .0001$, $d = 2$; $\Delta EV = 1.75$ 0.6 ± 0.4 , $t(560) = 9$, $p < .0001$, $d = 0.4$). Additionally, the $\Delta EV = 1.75$
 290 Lottery context presented evidence of significant between-country differences, absent in RL (**Fig**
 291 **2.E, right**; Country x Decision Context interaction: $\chi^2 = 68$, $DF = 30$, $p = <.0001$, see **Supplementary**

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292 **Materials** - Table S6 for post-hoc pairwise contrasts). In order to directly compare between
 293 descriptive and experiential choices at the $\Delta EV = 1.75$ context, we modelled preferences in this
 294 decision context by including an additional regressor (Decision Type; levels: RL, Lottery). Results
 295 indicated a significant Decision Modality effect ($\chi^2 = 216$, $DF = 1$, $p = <.0001$) that confirmed the
 296 difference between the two tasks.

297
 298 Overall, results from the Lottery task illustrated two important points. First, we were able to
 299 detect significant across country behavioural differences in our sample. This excludes that
 300 absence of effect in the RL task can thus not be ascribed to a general inability of detecting
 301 behavioural differences with our protocol. Second, these findings showed that risk aversion, as
 302 inferred from preferences expressed in the Lottery task, could not account for preferences in the
 303 RL task. This was specifically true for the key $\Delta EV=1.75$ decision context, where we observed a
 304 clear case of preference reversal when comparing the two decision modalities⁴⁵.

305 306 **Computational results**

307 To quantify the observed decision-making strategies in a systematic manner that encompassed
 308 all decision contexts across all tasks, we formalized choice behaviour using simple models built
 309 around the notion of subjective outcome scaling. This choice was motivated by the fact that this
 310 outcome scaling process, described below, could satisfactorily and parsimoniously capture the
 311 behavioural consequences of both context-dependent outcomes (in RL) and decreasing marginal
 312 utility (in Lottery). In both tasks, the subjective value of a given outcome or payoff was adjusted
 313 through the implementation of a free parameter ($0 \leq \nu \leq 1$) as follows:

$$314$$

$$315 \quad R_{scaled,t} = \begin{cases} 10p * \nu, & \text{if } R_{obj,t} = 10p \\ R_{obj,t} & \text{otherwise} \end{cases}$$

316
 317 where $R_{scaled,t}$ represented the scaled subjective outcome and $R_{obj,t}$ the objective unscaled
 318 outcome at trial t . For RL trials, we embedded the scaling process within a fully-parameterized
 319 version of the standard Q-learning algorithm, where option-dependent Q-values were learnt
 320 from the range-adapted reward term R_{scaled} . The algorithm also included free “temperature” [β],
 321 “forgetfulness” [φ] and “learning rate” [α] parameters, inasmuch as the RL process consists of
 322 acquiring value from experience and subsequently storing those values in memory for value
 323 actualization and learning¹¹. For the Lottery task trials, we formalized choice behaviour based on
 324 the subjective expected value that participants attributed to each choice as a function of its
 325 inherent risk, by multiplying $R_{scaled,t}$ by reward probability (as customarily done in standard linear
 326 utility models⁴⁶). While we did retain choice temperature [β] for this instance of the model, no
 327 memory actualization or learning processes were expected to take place during Lottery, which
 328 rendered φ and α unnecessary. We differentiated between scaling and temperature in RL and

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329 Lottery decision contexts by fitting specific parameters as v_{RL}, β_{RL} and v_{LOT}, β_{LOT} , respectively. We
330 made sure that our fitting procedure allowed us to correctly recover the parameters in simulated
331 datasets, as well as produce simulations that would closely replicate the observed behavioural
332 data (see **Supplementary Materials** for procedure and results of simulations and parameter
333 recovery).

334 Utilizing the same scaling parameter [v] in both models was a crucial step in the formalization, as
335 it allowed us to compare experiential and descriptive adaptation mechanisms in the same terms,
336 while integrating all the possible decision contexts. We expected v_{RL} to reflect context-dependent
337 range-value adaptation in the RL task, and v_{LOT} to capture marginally decreasing utility (and
338 therefore risk aversion) in the Lottery task. It follows that v_{RL} was expected to remain invariant
339 across country samples, confirming that relative value-encoding occurred universally, and
340 independently of risk preferences. Conversely, we expected v_{LOT} to differ significantly between
341 countries, in line with the observed risk aversion behaviours for each country sample, and to be
342 decorrelated from v_{RL} .

343 As shown in **Fig. 3A**, scaling patterns conformed to these hypotheses. First, we found minimal
344 evidence for differences between countries in v_{RL} ($v_{RL} \sim \text{Country}$; $SS = 0.98$, $DF = 10$, $p = 0.07$). We
345 confirmed this lack of effect through AICc weight ratio analysis: we considered a full model
346 including Country as a predictor, and as null an identical model not including it. Results strongly
347 disfavoured Country as a relevant predictor of v_{RL} in terms of information loss (i.e. full model
348 having 0.23 times the strength of the null model). Second, evidence showed that v_{LOT} differed
349 significantly across country samples ($v_{LOT} \sim \text{Country}$; $SS = 3$, $DF = 10$, $p < 0.01$). Here, AICc weight
350 ratio strongly favoured the Country effect model (full model being 16.65 times stronger than the
351 null model). Finally, as seen in **Fig. 3B**, between-country pairwise contrasts revealed significant
352 differences in v_{LOT} (see **Supplementary Materials - Table S9** for post-hoc pairwise contrasts).
353 Indeed, v_{LOT} differed substantially across countries, from quite substantial risk aversion (median
354 $v_{LOT} = 0.28$ in the Chilean sample) to moderate-high (median $v_{LOT} = 0.62$ in the Israeli sample).
355 Crucially, v_{LOT} values were highly correlated with the risk aversion behavioural patterns previously
356 observed in the $\Delta EV = 1.5$ and $\Delta EV = 1.75$ Lottery trials ($R = 0.84$ (95% CI = 0.81, 0.86) and $p <$
357 $.0001$; $R = 0.64$ (95% CI = 0.59, 0.69) and $p < .0001$), and decorrelated from v_{RL} ($R = 0.08$ (95% CI
358 = 0, 0.16) and $p = 0.24$) (see **Supplementary Materials - Fig. S4, Table S7**).

359 In sum, our computational approach confirmed strong evidence for stable cross-country
360 outcome context-dependence in the RL task using a compact computational measure. A similar
361 analysis performed in the Lottery task, confirmed that the preferences in the RL task could not
362 be accounted for risk aversion inferred from the Lottery task. Crucially, these results also
363 confirmed a difference in the stability of experience- and description-based processes across
364 countries.

365

366 In order to discard that the differences found in scaling between phases could be confounded by

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367 differences in task performance (i.e., lack of learning, inattention), we reanalysed and refitted
368 the data after excluding all participants who had less than 100% accuracy in choices involving
369 fully-dominated options in the Lottery task (as seen in previous studies on economic
370 preferences^{47,48}). In such contexts (i.e. $\Delta EV = 7.25$ and $\Delta EV = 9$), suboptimal choices can be
371 ascribed to general inattention, or the use of task-irrelevant heuristics (e.g. basing choices on a
372 cue's visual features, etc). These analyses, available in the Supplementary Materials section,
373 confirmed that this strict elimination criterion improved overall performance (and resulted in less
374 stochastic choices as proxied by the increase of both β_{RL} and β_{LOT}). However, even after exclusion
375 of these participants (n = 124 Total remaining n = 437), we were still able to replicate all
376 behavioural and computational patterns of results presented thus far (see **Supplementary**
377 **Materials - Figs S5-S8**).

378

379 **Drivers of risk aversion differences**

380 Our main goal was to test whether the behavioural and computational signatures of context-
381 dependent outcome encoding in RL would replicate across samples from different countries and
382 cultural backgrounds, and whether or not said preferences would differ from those of a
383 description-based task. We indeed found positive evidence showing that context-dependence as
384 captured in experience-based decision-making tasks is stable across the included countries and
385 distinct from risk aversion in tasks from description. Importantly, we did not have any specific
386 directional prediction on what cultural or socio-economic factors would influence preferences in
387 general (and more specifically, risk aversion in the Lottery task). However, in an exploratory
388 manner, we evaluated if the cultural and socio-economic metrics we had obtained characterized
389 the differences in risk aversion between samples. We did so by producing separate linear
390 regressions of the scaling (v_{RL} and v_{LOT}) and temperature (β_{RL} and β_{LOT}) parameters against our
391 country-level and subject-level cultural, economic and cognitive metrics. Results of these
392 exploratory analyses (see **Supplementary Materials - Table S12**) showed that single-dimension
393 subjective metrics did not significantly predict the values of the outcome scaling parameters, for
394 either task. On the other hand, country-level macrometrics composed of multiple dimensions
395 (i.e. HDI, Cultural Distance) did improve the models. This fell in line with previous findings on
396 intercultural risk preferences, which show that individual differences rarely inform risk
397 preferences, but country-level macrometric indexes are marginally better^{5,34,35}. It should be
398 noted however that even when significant, the correlation magnitudes were considerably small.
399 Nonetheless, it should be noted that cultural metrics generally predicted changes in v_{LOT} , but not
400 v_{RL} , which was consistent with the robustness of RL biases to cultural factors, as well as the gap
401 between experiential and descriptive choices found in our main results.

402

403

404 **Discussion**

405
406 In the present work, we sought to assess the cross-cultural stability of a recently discovered but
407 well-documented feature of human behaviour: context-dependent value encoding. It is
408 important to underscore that however robust, the vast majority of the results concerning context
409 effects in human RL come to date from WEIRD samples^{16,21,22,23,24,25,26,49}. This severely limits the
410 interpretation of context-dependent value encoding as a fundamental cognitive building block of
411 human choice behaviour in general. Here, we aimed to address this issue by showing marked
412 evidence of outcome context-dependence in samples from 11 countries of different sociocultural
413 makeup. Outcome context-dependence was evident both from behavioural signatures (i.e.,
414 magnitude invariant performance in the Learning phase; persistent suboptimal preferences in
415 the Transfer phase), and from the analysis of the key parameter of our computational model (i.e.,
416 v_{RL}). In addition to our RL task, we also administered a description-based task featuring the same
417 decision contexts. This allowed us to demonstrate for the first time that risk aversion (as
418 standardly inferred in behavioural economics from lottery tasks) could not account for
419 behavioural signatures of context-dependence in the RL task (especially suboptimal preferences).
420 Further, we have also shown that while experience-based processes and preferences were
421 remarkably stable across the included countries, description-based processes were not.
422 By replicating the finding of value context-dependence outside the WEIRD space, our work shows
423 that this cognitive process is not likely to be a simple cultural artefact^{50,51}. Of course, we
424 acknowledge that our current sample is not diverse enough to argue for a *definitive* universality
425 of contextual value encoding in RL. We also acknowledge that our samples may be neglecting
426 within-country variations (some of the included countries contain within themselves very
427 different ethnic and linguistic communities that we did not cover). However, the fact that our
428 results would show this bias consistently throughout samples constitutes strong evidence in that
429 direction, particularly since our samples were distinct enough to elicit between-country
430 differences in explicit value-based choices. Future research efforts seeking to extend the present
431 findings should consider testing in rural vs urban population setting⁵², and across different social
432 layers within the same societies².
433 The presence of context-dependent value learning across such a diverse sample falls in line with
434 numerous prior findings pointing to the reliability of the phenomenon. Multiple studies have
435 shown the flexibility of context dependence across different contexts³⁶, its validity for non-binary
436 outcomes²⁴ and non-binary decision spaces⁵³, and different temporal learning dynamics⁵⁴.
437 Furthermore, instances of context-dependent value learning have also been observed reliably in
438 a wide range of non-human animals, as diverse as mammals, birds and insects^{38,55}. The
439 coincidence between our present cross-cultural results and the ample array of cross-species prior
440 findings, reinforces the notion that RL processes may be largely hard-coded and evolutionary
441 stable⁵⁶. Indeed, despite the incidental generation of suboptimal preferences (e.g., in the

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442 Transfer phase), context-dependent value learning likely presents an overall adaptive value.
443 Theoretical propositions suggest that the normativity of context-dependent value learning can
444 be traced to at least two, not mutually-exclusive sources. First, it is possible that outcome-context
445 dependence in RL may constitute just another manifestation of the adaptive coding
446 phenomenon^{28,29}. In adaptive coding theory, the neural representations of objective variables
447 are transformed as a function of their underlying distribution, as a means to adjust to neural
448 constraints in information processing^{30,57,58}. Second, it is also possible that context-dependent
449 value learning serves the purpose of maximizing performance (i.e., “fitness”) in many ecological
450 foraging situations⁵⁹. Namely, encoding the *convenience* of a choice with respect to its
451 alternatives in context (i.e. storing the result of a computation rather than all of its components)
452 would be much less resource-intensive and ecological than committing to memory large
453 repertoires of absolute values dissociated from their contexts⁶⁰.

454
455 A crucial contribution of the present work is the analysis of behavioural performance in a
456 description-based decision-making task featuring the same decision problems as in the Transfer
457 phase (in addition to other benchmark decision problems). This allowed us, first and foremost,
458 to rule out the possibility that an absence of cross-cultural variation in context-dependent value
459 learning could be merely due to our inability to detect *any* cross-cultural differences in choice
460 behaviour in our sample. This was not the case, as we observed that behavioural preferences
461 elicited during the Lottery task were significantly different across countries, and in line with each
462 sample’s risk preferences. As with previous cross-cultural studies on decision-making, differences
463 in lottery-elicited risk preferences were found to be multicausal^{5,34,35}. Possible causes for this lack
464 of clarity in the etiology of risk preferences can be traced to the diversity of methods used to
465 quantify risk aversion across studies, and to the fact that most of the tested predictors evaluated
466 so far have been shown to account for only small fractions of the total variance³⁵. As stated,
467 pinpointing the cultural drivers of differences in risk preferences across countries was beyond
468 the scope of the present work. Given their effect size and exploratory nature, these results can
469 not be interpreted at the moment as anything more than venues for future research. Still, our
470 findings highlight the necessity of developing a unified strategy for quantifying risk preferences,
471 that may take into account the socio-economic, demographic and cognitive characteristics of
472 intercultural samples⁶¹.

473 Importantly, the addition of an explicit set of decision problems homologous to those of the RL
474 task allowed us to compare experience-based and description-based choice behaviour. This led
475 us to show, to the best of our knowledge for the very first time, that in otherwise comparable
476 decision contexts, risk aversion as inferred from a standard lottery task does not explain
477 preferences in the Transfer phase of a RL task. This was particularly noteworthy for the $\Delta EV =$
478 1.75 decision context, in which suboptimal choice preferences are customarily considered a
479 hallmark of context-dependence in value learning^{23,26,38}. Indeed, in the present work, preference

480 reversal in this context was observable for all countries during RL, and shown to be different from
481 risk-driven choice behaviour, thus calling for an alternative explanation.

482 These differences between the RL and Lottery tasks, concerning both subjective outcome
483 encoding and cross-cultural stability, were well recapitulated by our modelling approach. We
484 devised a simple parsimonious outcome-scaling process, that fitted to both experiential and
485 described versions of our decision problems, leading to the emergence of two clearly
486 distinguishable sets of values for the scaling parameter. It is important to underscore that, while
487 for parsimony and commensurability purposes, we modelled preferences in RL and Lottery tasks
488 with the same outcome-scaling model, this does not imply the assumption that both tasks share
489 similar computational processes. Indeed, based on the present and other behavioural
490 findings^{13,21,26} it is likely these different value scaling schemes arise from different underlying
491 computations altogether, respectively, outcome range-adaptation in RL and diminishing marginal
492 utility in Lottery (see **Supplementary Materials** for further considerations). It is nonetheless
493 important to note that here we are not claiming that context-dependent valuation is exclusivity
494 of experience (or reinforcement) based choices. In fact, many contextual effects have been
495 documented in descriptive choices (such as the decoy effect). Further studies should determine
496 whether such effects of description-based choices are cross-culturally stable.

497 The present results broadly fit within the larger framework of the experience-description gap, by
498 showing that preferences for the same decision problems are strongly affected by the modality
499 in which the problems are presented^{6,7,62}. This begs the question of whether or not differences
500 in probability weighting, which are robustly reported between experience-based and description-
501 based decisions, could explain the observed discrepancy, and more specifically, the preference
502 reversal in the $\Delta EV = 1.75$ decision context⁸. *Prima facie*, the fact that the “1 point with 75%
503 chance” option would be preferred to the “10 points at 25% chance” option, is compatible with
504 the traditional experience-based pattern of underweighting rare events^{7,63}. However, it should
505 be noted that for the preference reversal to derive solely from different probability weightings it
506 would require a probability distortion much larger than what has commonly been observed in
507 experiments and meta-analysis to date^{8,64}. Furthermore, the Learning phase of our experience-
508 based task featured complete feedback, a manipulation that makes feedback information
509 independent from choice, and thus reduces or even eliminates insufficient probability sampling
510 (which is the traditional explanation for the classical probability weighting of experience-based
511 choices). Finally, the underweighting of rare events would not explain the absence of a
512 magnitude effect during the RL Learning phase. Conversely, outcome context-dependence does
513 provide a satisfactorily and parsimonious explanation for the observed choice patterns in both
514 the Learning and Transfer phases.

515 Finally, we offer some reflection on the implications of our findings for behavioural science-
516 inspired interventions in policy-making. In recent years, the idea that descriptive models of
517 behavioural decision-making should be used to inform better policies (top-down), or for

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518 designing better decision architectures (bottom up) has gained traction^{65,66,67}. In the long-term,
519 this approach may help improve both individual and collective decision-making in domains where
520 biases and suboptimal decision-making represent key bottlenecks (e.g., issues such as choice of
521 vaccination, or behaviours favouring environmental protection). Historically, decision models in
522 (behavioural) economics, nudging and behaviourally-inspired policies have been based on
523 description-based choice behaviour. Our results show that, compared to description-based
524 processes, experience-based decision models are much more stable on a cross-cultural level,
525 possibly capturing deep and preserved features of human cognition. We therefore believe that,
526 especially if this pattern is confirmed and generalized to other tasks and processes, the present
527 work calls for a better consideration of experience-based decision models in designing
528 behavioural science-informed public policies in general.

529

530

531

532 **Methods**

533
534 *Participants:* Recruitment was conducted locally, through the standard channels of each
535 participating institution (e.g. dedicated mailing lists, flyers and online ads). Sample size was
536 determined through a power analysis based on the behavioural results of Bavard et al., 2021
537 online experiment²⁶. In the $\Delta EV = 1.75$ context of said experiment (blocked trials, complete
538 feedback version), online participants reached a difference between choice rate and chance (0.5
539 of 0.27 ± 0.30 (mean \pm SD). To obtain the same difference with a power of 0.95, the MATLAB
540 function “samsizewr.m” indicated that 46 participants per country were needed. Samples were
541 allowed to exceed this limit by up to 20%, to ensure the desired power would be achieved
542 regardless of potential participant exclusions. Exclusion criteria consisted of failure to complete
543 the task ($n = 43$) and troubleshooting/translation issues during the online task rollout ($n = 19$). A
544 remainder of $n = 561$ participants (342 female; mean age(SD) = 24.4(4.6)) composed the final
545 sample.

546
547 *Ethics:* research was carried out following the principles and guidelines for human
548 experimentation provided in the Declaration of Helsinki (1964, revised in 2013). This study
549 belongs to a series of experiments approved by the INSERM Ethical Review
550 Committee/IRB00003888 on 13 November 2018. Wherever needed, this ethical authorization
551 was seconded with further authorizations at the local level at the behest of each participating
552 institution. All participants provided written informed consent before their inclusion.

553
554 *Payment:* To sustain motivation throughout the experiment, participants were given a bonus
555 depending on the number of points won in each task. To ensure motivation would be even across
556 countries, each participating institution calculated the average cost of a local university lunch
557 (inter-country average cost in euros: 5.8 ± 2.82), and divided it by the total amount of points to
558 be potentially won throughout the experiment (i.e. 1275 points for a perfect run; average value
559 of point in euros: 0.0045 ± 0.002 ; average bonus reward obtained in euros: 5.4 ± 1.53). In addition
560 to the bonus accrued through point accumulation, all participants received a flat participation
561 rate equivalent to an additional student lunch (see **Supplementary Materials - Table S2** for
562 average bonuses in local currencies).

563
564 *Behavioural task:* there were two behavioural tasks, the Reinforcement Learning (RL) task and
565 the Lottery task (**Fig 1.A**). The RL task was a direct reproduction of the probabilistic instrumental
566 learning task performed in Experiment 7 of Bavard et al., 2021²⁶. Participants were asked to
567 choose on a trial basis between the undisclosed lotteries of different 2-armed bandit problems,
568 with the goal of maximizing overall reward. The Lottery task consisted of a standard economic
569 decision-making task, where participants had to choose on a trial basis between two lotteries of

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570 known expected value, again with the intention of maximizing overall reward.
571 In the RL task, the lotteries for each decision context were represented by abstract stimuli (cues)
572 taken from randomly generated identicons. Identicons were generated so that hue and
573 saturation had similar values within the HSLUV colour scheme (www.hsluv.org). In the Lottery
574 task, cue cards displaying the reward and probability values for each option were used instead.
575 For all tasks, each decision context was formed by two cues, one at each side of the screen,
576 equidistant to the screen centre. Each trial consisted of a single decision context. Stimulus
577 location was pseudo-randomized, so that every cue would appear an equal number of times on
578 each side of the screen.

579 In the RL task, participants had to complete a Learning phase, and then a Transfer
580 phase^{16,21,22,23,24,25,26,49}. In the Learning phase (**Fig. 1B, upper**), cues appeared in four different
581 fixed pairs (i.e. decision contexts). Within pairs, each cue would lead to possible zero and non-
582 zero outcomes with reciprocal probabilities (0.75/0.25 and 0.25/0.75). Each decision context
583 featured only two possible outcomes: either 10/0 points or 1/0 points. Contexts were labeled by
584 taking into account the difference in expected value between options (i.e., two $\Delta EV = 5$ and two
585 $\Delta EV = 0.5$ decision contexts). Once a choice was made by clicking on a cue, a fixed 500 ms delay
586 ensued, after which factual and counterfactual choice feedback was displayed for 1000 ms in the
587 form of “10,” “1,” or “0” points cue cards. After Learning phase completion, the subtotal of points
588 earned was displayed, together with its monetary equivalent in local currency. In the Transfer
589 phase, cues were rearranged into four new pairs ($\Delta EV = 7.25$, $\Delta EV = 6.75$, $\Delta EV = 2.25$, and $\Delta EV =$
590 1.75). Crucially, the probability of obtaining a specific outcome from each cue remained the same
591 as in the Learning phase (**Fig. 1B, lower**). In the Lottery task (**Fig. 1C**), participants had to choose
592 between explicit cue cards, which were paired reproducing the 4 decision contexts of the
593 Transfer phase, and another 4 decision contexts comparing varying probabilities of winning 10
594 points (100%, 75%, 50%, 25%) versus the certainty of winning 1 point ($\Delta EV = 9$, $\Delta EV = 6.5$, $\Delta EV =$
595 4 , $\Delta EV = 1.5$). Neither Transfer phase nor the Lottery task presented any post-choice feedback:
596 choices were followed by a fixed 500 ms delay interval, after which “???” cue cards were
597 displayed for 1000 ms. Each decision context of the RL task (4 in Learning phase, 4 in Transfer
598 phase) was presented 30 times, for a total of 240 trials. Decision contexts of the Lottery task (4
599 reproducing Transfer, 4 benchmarking risk aversion) were presented 4 times each, for a total of
600 32 trials. Presentation order of decision contexts was pseudo-randomized within each phase, so
601 that all trials of a given decision context would be clustered (i.e., “blocked” stimuli
602 presentation).

603
604 *Questionnaires:* after completing the behavioural experiment, participants were required to
605 complete several psychometric and socioeconomic questionnaires. Socioeconomic
606 questionnaires included the Individualistic and collectivistic tendencies inventory⁴², the
607 perceived Socioeconomic status in childhood, adulthood and social hierarchy questionnaires⁴¹,

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608 and the Centrality of religiosity questionnaire⁴³. The sole goal of these questionnaires was to
609 confirm that samples were socioculturally different from each other, as simply belonging to
610 different countries may not have ensured a difference. Psychometric questionnaires were
611 incorporated for purely exploratory purposes, including the Ten Item Personality Inventory
612 (TIPI)⁶⁸ and the extended version of the Cognitive Reflection test (CRT)⁴⁴. Order of questionnaires,
613 and questions within each questionnaire, were randomized (see **Supplementary Materials** for a
614 technical description of each questionnaire, and exploratory analyses).

615
616 *Country metrics:* questionnaires gave us the opportunity of assessing different dimensions of the
617 socioeconomic and cultural makeup of each country sample from participants' own subjective
618 answers. To quantify the socioeconomic and cultural profile of each country sample in a
619 macrometric way, we also incorporated into the analysis each country's Human Development
620 Index score³⁹, and the Cultural Distance between countries⁴⁰. Both of these coefficients are
621 computed from combining large numbers of economic, educational, political and psychosocial
622 markers. Under the same rationale as questionnaires, inclusion of these metrics was not
623 hypothesis-driven, but rather served to establish the differences between country samples and
624 conduct exploratory analyses (see **Supplementary Materials** for details on metrics).

625
626 *Procedure:* Testing was conducted in a hybrid face-to-face/online format, where participants met
627 a local experimenter for an online live debrief held in their local language to verify identity and
628 cultural affiliation. After the interview, participants received a personalized link to a Gorilla server
629 (www.gorilla.sc) where the experiment was hosted. After clicking on the link, participants were
630 sent to a consent form, which they had to complete in order to access the actual experiment. The
631 experiment started by providing written instructions on how to perform the task. It was explained
632 to participants that they would have to choose between two different options over several trials,
633 with the goal of maximizing overall point reward. It was told to them that they would have to
634 make this decision without necessarily knowing the probability and magnitude of rewards for
635 each option at first. Finally, it was explained at length that their final payoff would be affected by
636 their choices, as rewards were convertible to actual currency. The possible outcomes in points
637 (0, 1, and 10 points) were explicitly shown, as well as the point-currency conversion rate for their
638 country (e.g. 1 point = 0.005 euros in France; see **Supplementary Materials - Table S2**).
639 Instructions were followed by a short training session of 12 trials, designed to familiarize
640 participants with response modality. Participants could decide to repeat the training session up
641 to two times prior to starting the actual experiment. After finishing the training session,
642 participants had to complete the RL task (Learning and Transfer), the Lottery task and the
643 sociocultural questionnaires, in that order. The existence of the Transfer phase was not disclosed
644 until the end of the Learning phase, to prevent the use of alternative strategies. Crucially, before
645 starting the Transfer phase, participants were made explicitly aware of the fact that they would

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646 be presented with the same cues they had seen during the Learning phase, but combined in
647 different pairs. Before starting the Lottery task, participants were shown an example of a cue
648 card with its explicit reward probability and magnitude written on it, and were again instructed
649 to choose the option that they thought would maximize overall point reward. Following
650 completion of the Lottery task, participants had to answer all sociocultural and psychometric
651 questionnaires. Order of questionnaires as well as order of each item within questionnaires were
652 randomized. Completing the full experiment, including consent and questionnaires, took
653 approximately 25 minutes (average response time per trial 1.46 ± 6.7 s; median 0.96 s). Once
654 finished with the experiment, participants were given a personalized completion code, and were
655 tasked with sending this code to the experimenter by email to signal completion and trigger
656 payment. The online debrief, task instructions, and questionnaires were all delivered in each
657 country's official language, by local researchers.

658
659 *Statistical analyses:* All statistical analyses were performed and visualized using R^{69,70,71}. The main
660 dependent variable was the correct choice rate, i.e., choices directed toward the option with the
661 highest expected value. Statistical effects were assessed by phase, using generalized linear
662 mixed-effect models with a random intercept per participant⁶⁹, with decision context and country
663 of sample as categorical predictors (i.e. $P(\text{correct}) \sim \text{Decision Context} \times \text{Country} + \epsilon$, see
664 **Supplementary Materials** for model selection). P-values were computed through Analysis of
665 Deviance (Type II Wald χ^2 test): we reported χ^2 , degrees of freedom and P-values. Proportion of
666 variance explained per predictor was not reported because of how variance is partitioned in
667 mixed models⁷². In cases where only one data point per participant was available (e.g. differences
668 in parameter values across countries), statistical significance was evaluated through standard
669 linear models using country as a categorical predictor (e.g., $v_{RL} \sim \text{Country}$). For those analyses, we
670 reported F-statistic, Sum of Squares, P-value and Cohen's F. Post-hoc contrasts were calculated
671 with their respective confidence intervals, through estimated marginal means analysis, and P-
672 values were Benjamini-Hochberg corrected. In particular, whenever we had to assess whether
673 choice rate performances were significantly different from chance, we performed additional t-
674 tests against chance level (0.5). In those cases, we reported the t-statistic, P-value, and Cohen's
675 *d* to estimate effect size. The significant association between continuous quantities (e.g. between
676 parameter value and performance at a given decision context) was tested through correlation
677 analysis, where we reported T-statistic, degrees of freedom, P-values, and *R*-coefficient as effect
678 size. To prove lack of effect, we conducted AICc weight ratio analyses^{73,74} using a model
679 containing the tested predictor (full) and its equivalent minus said predictor (null).

680
681 *Computational analyses:* the SCALING model was built around the notion of value scaling. Value
682 scaling for both the RL and Lottery tasks was arbitrated by the free parameter (ν) designed to
683 capture value adaptation as follows:

684

$$R_{scaled,t} = \begin{cases} 10p * \nu, & \text{if } R_{obj,t} = 10p \\ R_{obj,t} & \text{otherwise} \end{cases}$$

685

686 where $R_{scaled,t}$ represented the scaled objective reward $R_{obj,t}$ at trial t , and $0 \leq \nu \leq 1$. For RL
 687 task trials, we used a simple Q-learning model¹¹ to estimate in each choice context (or state) the
 688 expected reward (Q) of each option and pick the one that maximizes this expected reward Q. At
 689 trial t , option values (for example of the chosen option c) were updated according to the delta
 690 rule:

691

692

$$Q(c)_{t+1} = Q(c)_t + \alpha_c * (R(c)_{scaled,t} - Q(c)_t)$$

693

694

695 where α_c is the learning rate for the chosen option, which, multiplied by the difference
 696 between the $R_{scaled,t}$ and Q_t is the prediction error term. We then modelled participants' choice
 697 behaviour using a softmax decision rule that yielded the probability that for a state s a participant
 698 would choose, say, option a over option b according to:

699

700

$$P(a)_t = \frac{1}{1 + e^{\beta * (Q(b)_t - Q(a)_t)}}$$

701

702 where β is the inverse temperature parameter. Low inverse temperatures ($\beta \rightarrow 0$) cause the
 703 action to be stochastically equiprobable. High inverse temperatures ($\beta \rightarrow +\infty$) result in choices
 704 deterministically determined by the difference between the Q-values¹¹. Our algorithm also
 705 included a forgetfulness parameter ϕ ($0 \leq \phi \leq 1$) that allowed us to account for the possibility
 706 of forgetting the option values when moving from the Learning to the Transfer phases of the RL
 707 task. The Q-values used to fit (and simulate) the Transfer phase choices ($Q(\cdot)_{TRA}$) were
 708 calculated from the Q-values of the Learning phase $Q(\cdot)_{LEA}$ as follows:

709

710

$$Q(\cdot)_{TRA} = Q(\cdot)_{LEA} * \phi$$

711

712

713 For Lottery task, expected utilities EU of individual lotteries were calculated based on the
 714 described probability (p) its non-zero outcome and the subjective rescaled rewards ($R_{scaled,t}$,
 715 calculated as for the Learning task). For example the expected value of lottery a was calculated
 716 as follows:

717

718

$$EU(a) = R(a)_{scaled,t} * p(a)$$

719

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720 Choice probabilities were also instantiated through a softmax rule, as follows (probability of
721 choosing lottery a , over letter b):

722

$$723 \quad P(a)_t = \frac{1}{1 + e^{\beta*(EU(b)-EU(a))}}$$

724

725 Since the lottery task does not involve learning or memory processes, its model lacked any notion
726 of learning rate and forgetting parameter. The RL and the Lottery model shared the scaling
727 parameter and the inverse temperature that were fitted specifically for each task (v_{RL} and v_{LOT} ;
728 β_{RL} and β_{LOT}).

729

730 Model parameters were fitted using maximum likelihood estimation using gradient descent as
731 implemented in Matlab. Finally, in the **Supplementary Materials - Alternative Models** section
732 we compared SCALING to three alternative computational models to discard other possible
733 interpretations of our data. These included the ABSOLUTE model, which encoded outcomes on
734 an absolute scale independently of the decision context in which they were presented; the
735 ABSOLUTE-RISK model, which rescaled rewards for the RL task trials using the v_{LOT} parameter
736 fitted on Lottery task trials, in order to evaluate whether risk aversion predicted preference
737 reversal; and the NEGLECT model, which assumed participants only learned the probabilities
738 behind each choice, but ignored reward magnitude.

739

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759

760 **Author contributions**

761 H.A. is the lead author and researcher responsible for study design, coordination and
762 management between teams, data management and collection, as well as analysis, visualization
763 and manuscript writing. S.B. was the main author behind the original design that this study
764 replicated, and greatly contributed to ensure that our design indeed reproduced theirs. F.B., D.B.,
765 F.C., M.C., M.G., E.J.G., D.K., M.K., G.L., M.S., J.Y and O.Z. reviewed and supported the design of
766 the experiment and its hypotheses. They also took charge of translation and deployment of the
767 experiment in each of their countries, collected data locally and revised the manuscript. B.B.,
768 J.S.C., U.H., A.B.K., J.L., C.OM., J.N., G.R., A.S-J., A.S., B.S. and K.W. are senior supervisors who
769 monitored the study locally, provided insight on the experimental design and commentary on
770 the final version of the manuscript. In addition, K.W. also provided essential scientific and logistic
771 support for deploying the experiment world-wide. S.P. was the main senior supervisor, who
772 worked hand in hand with H.A. on every aspect of this work including collaboration management,
773 design, hypothesis development, supervision of the analysis, interpretation of results,
774 visualization and writing.

775

776 **Competing interests**

777 The authors declare no competing interests. The authors did not receive any monetary
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782 **References**

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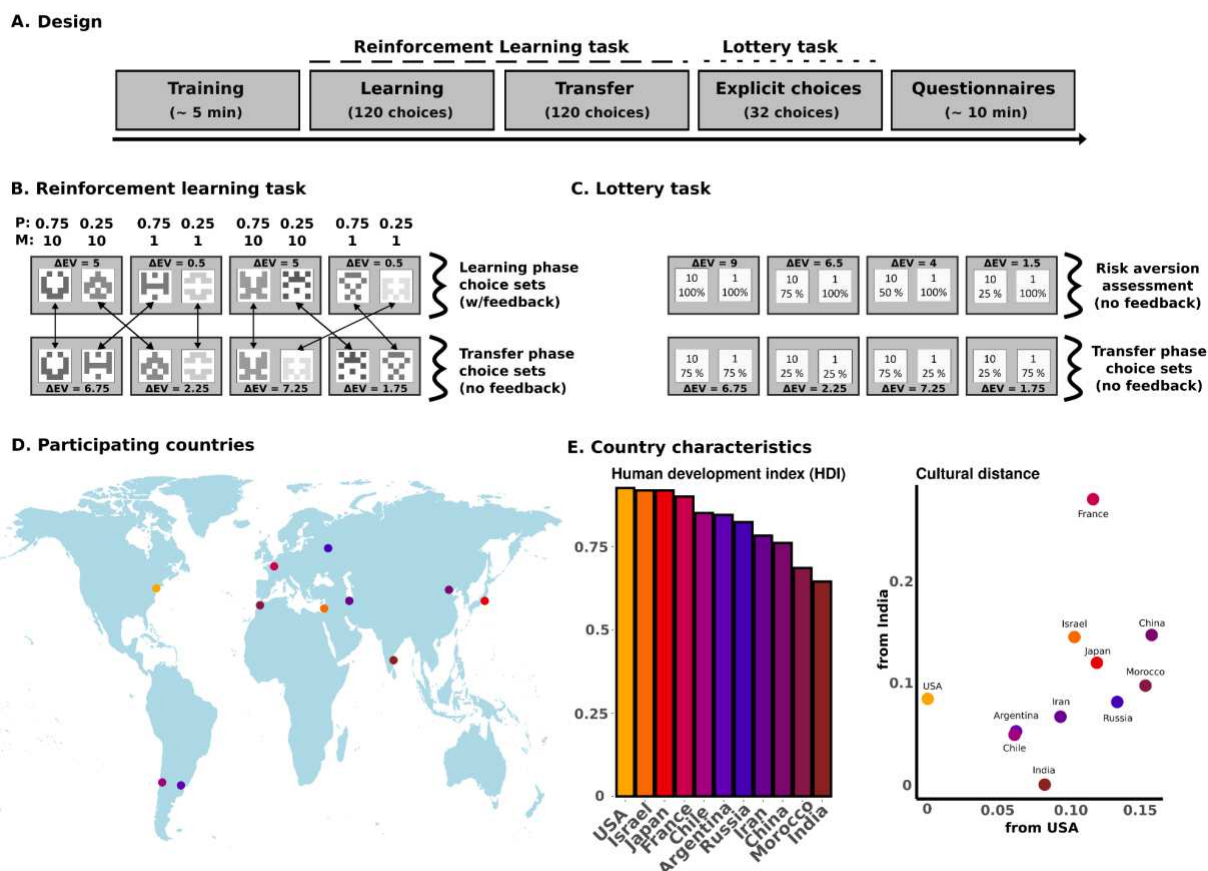
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964 **Figures and tables**

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968 **Figure 1: Behavioural protocol and sample. A. Design.** Outline of the experimental design, including969 training, RL task, Lottery task and questionnaires. **B. Reinforcement learning task.** Probabilities and

970 magnitudes of each of the lotteries for the Learning and Transfer phases, together with difference in

971 expected value between options for each local decision context. Complete feedback was provided during

972 the Learning phase (factual and counterfactual feedback); no feedback was provided during the Transfer

973 phase. **C. Lottery task.** Probabilities and magnitudes of each of the lotteries for the Lottery task, together

974 with difference in expected value between options for each local decision context. No feedback was

975 provided. **D. Participating countries.** Geographical location of the samples. Dots are placed on the city

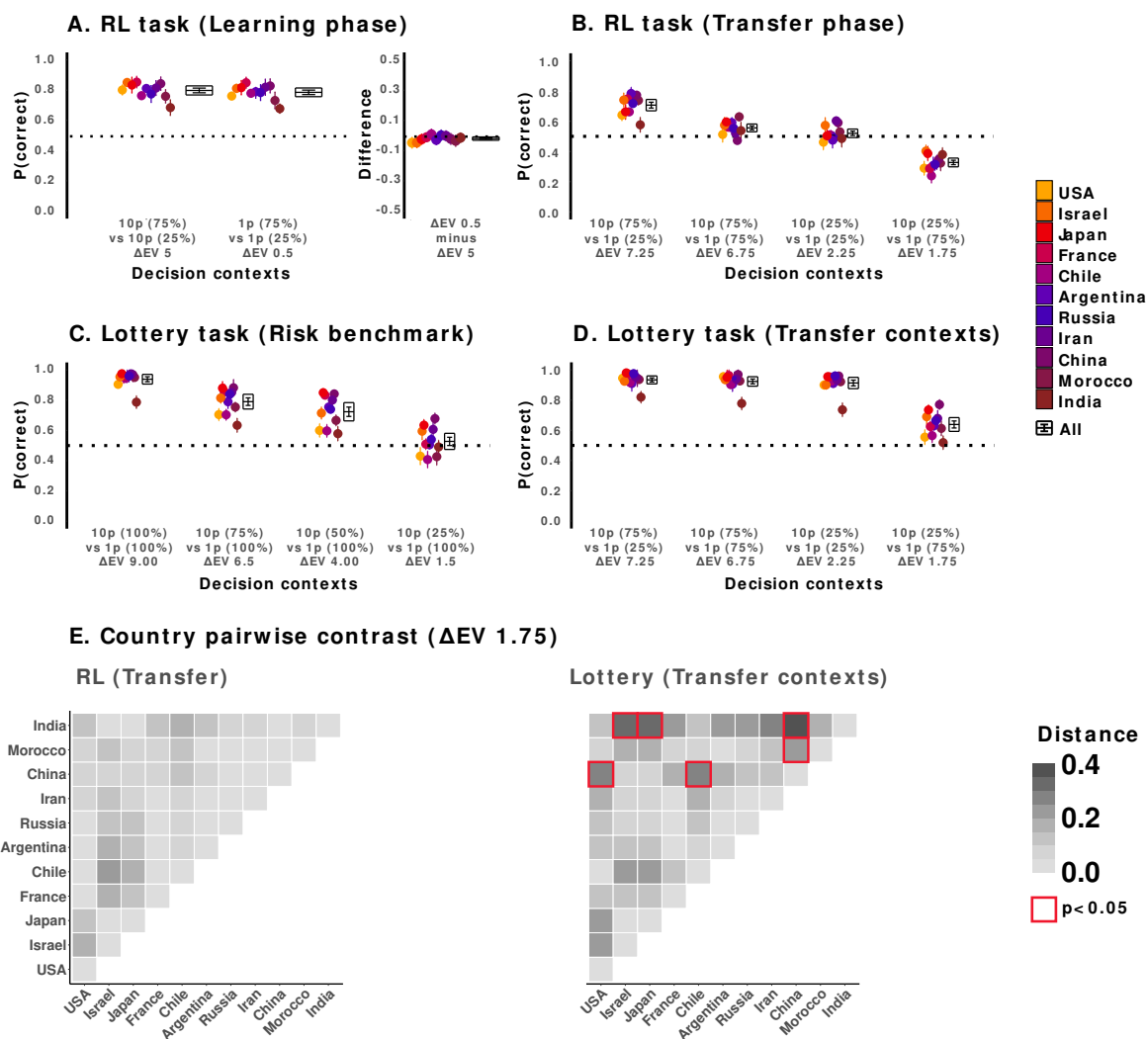
976 where data collection was conducted (New Jersey, Haifa, Tokyo, Paris, Santiago de Chile, Buenos Aires,

977 Moscow, Tehran, Beijing, Rabat, Chennai), color-coded as a function of their country's Human

978 Development Index scores (see panel E - right). **E. Country macrometric characteristics.** Human

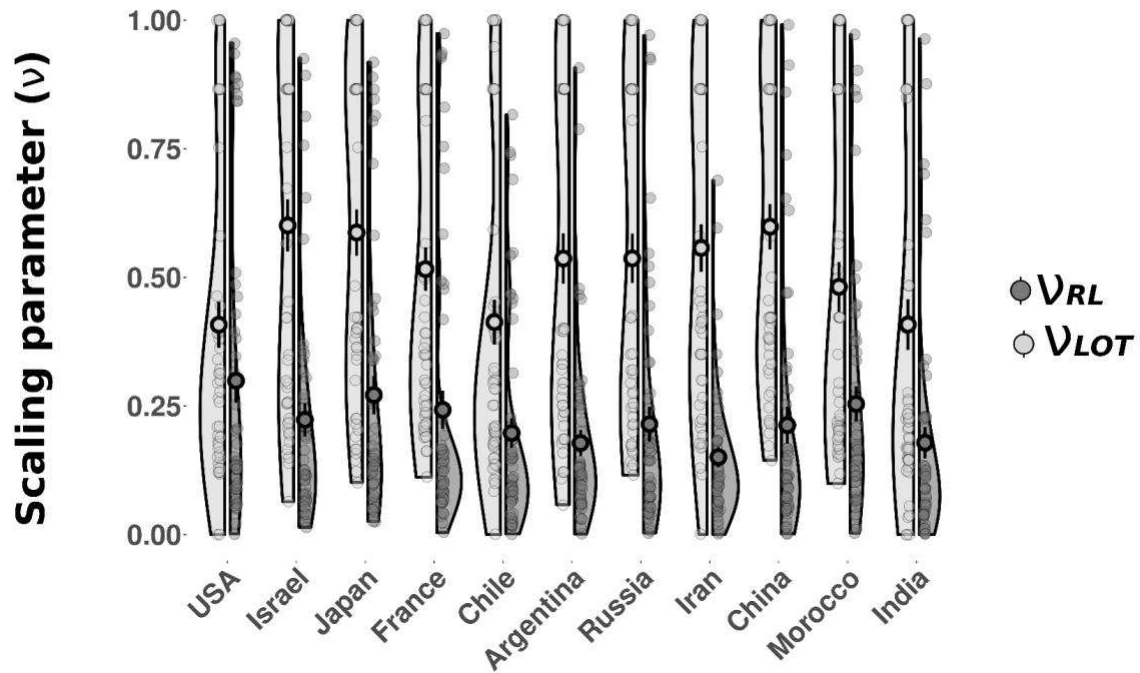
979 Development Index scores per country (left), and cultural distance between each country, India and the US

980 (right).

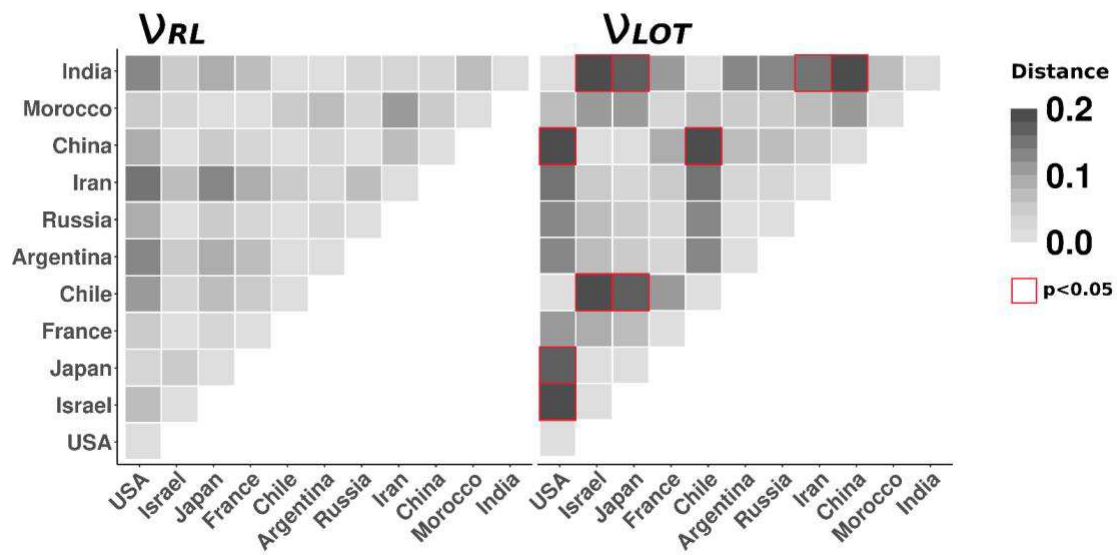


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 982 **Figure 2: Behavioural results. A. RL task (Learning phase).** Proportion of correct answers (i.e. choices
 983 that maximize expected value) for each individual country (dots) and the average of all countries (box) for
 984 each of the two decision contexts of the Learning phase. **B. RL task (Transfer phase).** Proportion of
 985 correct answers (i.e. choices that maximize expected value) for each individual country (dots) and the
 986 average of all countries (box) for each of the four decision contexts of the Transfer phase (leftmost part).
 987 Difference between the big ($\Delta EV=5.0$) and the small ($\Delta EV=0.5$) magnitude context (rightmost panel) **C.**
 988 **Lottery task (benchmark of risk preferences).** Proportion of correct answers (i.e. choices that maximize
 989 expected value) for each individual country (dots) and the average of all countries (box) for each of the four
 990 decision contexts of the Lottery task presented to estimate risk aversion. **D. Lottery task (Transfer**
 991 **decision contexts).** Proportion of correct answers (i.e. choices that maximize expected value) for each
 992 individual country (dots) and the average of all countries (box) for each of the four decision contexts of the
 993 Lottery task that were homologous to the decision contexts of the Transfer phase. **E. Country pairwise**
 994 **contrasts for the $\Delta EV = 1.75$ decision context.** Euclidean distance between mean proportion of correct
 995 answers of each country during the RL task (left). Euclidean distance between mean proportion of correct
 996 answers of each country during the Lottery task (right). *Bars represent standard error of the mean. Midline*
 997 *of box represents mean of all countries. Bounds of box represent the 95% confidence interval of the mean.*
 998 *Red boxes represent a significant pairwise contrast.*

A. Scaling parameter (v)



B. Country pairwise contrast (v)



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Figure 3. Computational results. A. Scaling parameter values. Values of the scaling free parameter estimated during the RL task (v_{RL}) and the Lottery task (v_{LOT}). **B. Country pairwise contrasts for the scaling parameters.** Euclidean distance between mean of scaling parameters of each country during the RL task (*left*). Euclidean distance between mean of scaling parameters of each country during the Lottery task (*right*). *Translucent dots are individual participants' values; underscored dots represent the mean, bar represents standard error of the mean. Red boxes represent a significant pairwise contrast.*

1007 **Table 1.** Demographic, sociocultural metrics and size of samples. *of the 78% of USA participants who
 1008 chose to disclose their education level. P-values are Bonferroni-corrected for the number of comparisons
 1009 presented in this table.

	USA	Israel	Japan	France	Chile	Argenti.	Russia	Iran	China	Morocco	India	ALL	P
N (initial)	51	58	55	58	59	51	58	60	53	56	64	623	--
Exclusions													
Completion issues	0	7	3	3	5	1	7	6	1	2	8	43	--
Rollout issues	1	1	2	1	0	0	1	5	3	3	2	19	--
N (final)	50	50	50	54	54	50	50	49	49	51	54	561	--
Age (mean(SD))	26.5(4.2)	26(2.9)	20.6(1.7)	28.9(5.7)	22.5(2.2)	22.5(3.6)	26.3(4.1)	27(5.4)	23.4(2.8)	21.8(2.9)	23.1(4.9)	24.4(4.6)	<.0001
Gender (% fem.)	74	70	58	67	65	72	50	65	49	47	53	60.9	.99
University education (%)	95*	100	100	100	100	100	100	100	100	100	100	--	
Human development Index 2019 (HDI)	0.926	0.919	0.919	0.901	0.851	0.845	0.824	0.783	0.761	0.686	0.645	--	
Cultural distance													
From USA	--	0.1060	0.1222	0.1195	0.0627	0.0638	0.1369	0.0959	0.1618	0.1573	0.0845	--	--
From India	0.0845	0.1454	0.12	0.2811	0.0491	0.0525	0.0814	0.0669	0.1474	0.0975	--	--	--
Socioeconomic Status (mean(SD))													
Childhood	3.9(0.3)	4.8(0.3)	6.1(0.2)	4.8(0.2)	5.9(0.3)	6.1(0.2)	4.3(0.3)	5.1(0.3)	4.2(0.3)	4.6(0.3)	5.2(0.3)	--	<.0001
Adulthood	3.9(0.3)	3.5(0.2)	5.7(0.3)	3.9(0.3)	4(0.2)	4.9(0.2)	4.2(0.2)	5.2(0.3)	4.8(0.3)	3.8(0.3)	5.1(0.3)	--	<.0001
Social hierarchy	5.4(0.3)	6.1(0.2)	7(0.2)	5.9(0.2)	6.7(0.2)	6.6(0.2)	5.5(0.2)	6.8(0.2)	5.2(0.3)	6.1(0.3)	6(0.3)	--	<.0001
Individualistic & collectivistic tendencies (mean(SD))													
Vertical Ind.	18(0.9)	22(0.8)	23(0.8)	18(1)	17(1)	18(1)	21(0.7)	23(0.9)	26(0.8)	25(0.9)	24(0.7)	--	<.0001
Horizontal Ind.	29(0.6)	28(0.7)	25(0.8)	28(0.6)	29(0.6)	27(0.7)	26(0.7)	31(0.6)	28(0.8)	31(0.5)	28(0.8)	--	<.0001
Vertical Col.	24(1)	26(0.7)	21(0.9)	24(0.7)	25(0.9)	19(0.7)	19(0.7)	21(1)	27(0.7)	30(0.8)	30(0.9)	--	<.0001
Horizontal Col.	28(0.8)	28(0.8)	26(0.9)	27(0.6)	31(0.6)	31(0.5)	25(0.7)	25(0.7)	26(0.7)	30(0.7)	28(0.8)	--	<.0001
Centrality of religiosity in social environment (mean(SD))													
Experiences	8(0.6)	6.8(0.5)	5.8(0.4)	6.8(0.5)	7.5(0.5)	5.7(0.4)	6.4(0.4)	9.1(0.5)	4(0.3)	13(0.4)	11(0.5)	--	<.0001
Role in ideology	9.9(0.6)	9(0.6)	8(0.4)	8.9(0.6)	10.5(0.4)	7.1(0.5)	8.3(0.6)	11(0.6)	5.3(0.4)	14(0.3)	11(0.5)	--	<.0001
Religious thought	7.6(0.4)	6.4(0.4)	7.7(0.3)	8.2(0.5)	6.6(0.4)	7.5(0.4)	7.3(0.4)	7.8(0.4)	5.8(0.4)	11(0.4)	9.1(0.5)	--	<.0001

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Private life	7.8(0.4)	6(0.5)	7.3(0.4)	6.9(0.5)	7.6(0.5)	5.9(0.4)	6.1(0.4)	7.7(0.6)	5.4(0.4)	12(0.5)	10(0.5)	--	<.0001
Public life	5.6(0.5)	6.2(0.5)	5.7(0.3)	5.9(0.4)	5(0.4)	4.7(0.4)	4.4(0.3)	5.4(0.4)	4.1(0.3)	9.2(0.5)	8.6(0.5)	--	<.0001

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Supplementary Files

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