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1 **Technical reasoning bolsters cumulative technological culture through**
2 **convergent transformations**

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14 **One-Sentence Summary:** Social learning with technical reasoning allow us to improve
15 technologies even when incomplete information is transmitted.

16

17 **Abstract**

18 Understanding the evolution of human technology is key to solving the mystery of our
19 origins. Current theories propose that technology evolved through the accumulation of
20 modifications that were mostly transmitted between individuals by blind copying and the
21 selective retention of advantageous variations. An alternative account is that high-fidelity
22 transmission in the context of cumulative technological culture is supported by technical
23 reasoning, which is a reconstruction mechanism that allows individuals to converge to
24 optimal solutions. We tested these two competing hypotheses with a micro-society
25 experiment, in which participants had to optimize a physical system in partial- and degraded-
26 information transmission conditions. Our results indicated an improvement of the system over
27 generations, which was accompanied by an increased understanding of it. The solutions
28 produced tended to progressively converge over generations. These findings show that
29 technical reasoning can bolster high-fidelity transmission through convergent transformations,
30 which highlights its role in the cultural evolution of technology.

31

32 **Introduction**

33 Today technology pervades human life, and it is often taken for granted that technology
34 and science progressively become more advanced and more refined through time. Yet, the
35 origin of this capacity remains a fascinating mystery. Other primates sometimes use tools
36 [e.g., chimpanzees (1), capuchins (2), orangutans (3)] and have sometimes been shown to be
37 doing so for very long periods of time (4). There is also evidence that, like humans, non-
38 human primates learn to use tools through social learning, by the observation of tool-using
39 conspecifics (5). However, human technology is strikingly different because non-human
40 primate tool use does not evolve and does not gradually become more efficient and more
41 complex through time (6). The term Cumulative Technological Culture (CTC) has been
42 coined to refer to the progressive increase in the complexity and/or efficiency of tools and
43 techniques that are too complex to be invented by a single individual (7–9). Interestingly,
44 there is increasing evidence that some non-technological aspects of animal culture can
45 cumulatively evolve (10–12), raising the question of how and why technology became
46 cumulative in humans and not in other primates.

47 CTC has been considered to be driven by two engines: High-fidelity transmission, the
48 similarity between tools and techniques across episodes of transmission [also called *episodic*
49 *fidelity*, see (13)], and innovation (14). The crucial role of high-fidelity transmission in CTC
50 has been repeatedly stressed with the rationale that, when an innovation appears, it will
51 quickly be lost if it cannot be faithfully transmitted to others (7, 15–19). High-fidelity-
52 transmission has often been assumed to result from unique social-cognitive skills that allow
53 humans to imitate or “infocopy” [(6, 18, 20, 21); also called high-fidelity copying or
54 *propensity fidelity*, see (13)]. Following this view, the role of causal reasoning in CTC has
55 often been minimized by assuming that complex technologies result from the accumulation of
56 many often poorly understood improvements made over generations (7, 22, 23) combined

57 with rare intentional improvements achieved through causal reasoning (24). Although the
58 term *causal reasoning* is widely employed in the literature, we have stressed (25) that the
59 term *technical reasoning* may be more appropriate in the field of CTC because it refers to a
60 specific form of causal – and analogical – reasoning directed toward the physical world. Thus,
61 the term technical reasoning will be hereafter used to refer to this specific kind of reasoning.

62 Importantly, the similarity observed between tools or techniques in CTC needs not
63 come from the existence of copying mechanisms (26, 27). An alternative explanation, the
64 cultural attraction theory (26, 28, 29), is that humans are endowed with cognitive mechanisms
65 that are not specifically designed for copying but that transform and adapt what is socially
66 learned to the ends and characteristics of the learning individual. Under such a view, high-
67 fidelity transmission is achieved through convergent transformations, that is, individuals with
68 the same goal will give rise to similar cultural products through shared cognitive skills, goals,
69 and environments (30, 31). This view has recently received support from theoretical,
70 experimental, and field studies on cultural evolution in humans (32–37) and non-human
71 primates (31, 38) and is also in line with studies on language evolution (39). For instance,
72 arguments transmitted along transmission chains could become degraded and then fully
73 reconstructed through deductive reasoning (40). With respect to CTC, the cultural attraction
74 theory translates into the fact that individuals use technical-reasoning skills to solve complex
75 technological problems and that high-fidelity transmission is the result of convergent
76 transformations.

77 To experimentally examine the role of convergent transformations *versus* copying
78 mechanisms in CTC, we used a recently developed task that was aimed at providing the sort
79 of complexity encountered in CTC. Derex et al. (22) reported a micro-society study designed
80 to investigate the role of causal understanding in CTC. The task consisted of optimizing a
81 wheel system (**Fig. 1A**). This task was multidimensional because the speed of the wheel

82 depended on its moment of inertia (i.e., a wheel with its four weights close to its center is
83 faster than a wheel with its four weights farther from the center) and the position of its center
84 of mass (i.e., the initial acceleration is better when the wheel is unbalanced with the center of
85 the mass located ahead and above the axis of the wheel; **fig. S1**). The participants performed
86 the task as members of chains of five participants (**Fig. 1B**). The experimenter transmitted to
87 each participant (except those of the first generation) the weight configurations and their
88 associated speeds from the last two trials of the previous participant (hereafter called
89 Configurations+Speed condition). Participants' understanding of the wheel system was
90 assessed with an understanding test consisting of selecting the fastest wheel configuration out
91 of several presented. The results indicated that the wheel system became progressively
92 optimized, and although Derex et al. (22) found no improvement in understanding, we
93 performed a partial replication (41) motivated by some methodological issues and
94 demonstrated that the improvement was linked to the participants' understanding of the
95 technology (i.e., their understanding increased through time, they were able to transfer this
96 understanding to other problems, and they were better than controls).

97 The findings reported in both Derex et al. (22) and our prior study (41) gave limited
98 insight into the process through which participants arrived at better configurations because the
99 participants had access to all the information they needed (wheel configurations and
100 associated speeds) to reproduce with high fidelity the wheel systems produced by their
101 predecessors. Nevertheless, our findings (41) indicated that even when individuals had access
102 to all the information needed to blindly copy, they formed a causal representation of the
103 physical system that they used to produce improvements. The role of technical reasoning may
104 appear redundant here but could reveal its full potential if the information transmitted
105 between individuals is incomplete or incorrect (25). Partial information combined with
106 technical-reasoning skills might allow an individual to converge toward the same technical

107 solution or another technical solution that maintains – or even improves – the technology
108 (25).

109 The present study aimed to test this possibility through two micro-society conditions, in
110 which participants had five trials to improve a wheel system, as described above (14 chains of
111 five participants in each condition; **Fig. 1, A and B**). After their five trials, the participants’
112 understanding of the physical system was assessed with an understanding test (twelve items
113 for center of mass and twelve for inertia). In the Speed-Only condition, the only information
114 that was transmitted to the next participant was the last two wheel speeds of the previous
115 participant in the chain (i.e., no information at all about the configurations associated; **Fig.**
116 **1C**). In the Configurations+Speed+Noise condition, the participants were given two weight
117 configurations and their associated speeds. The configurations came from the previous
118 participant in the chain but were modified by randomly changing the position of the four
119 weights closer to or further from the center of the wheel (**Fig. 1C**). Therefore, the participants
120 had access to partial or degraded information in both conditions. If copying is crucial for CTC
121 and technical reasoning is non-necessary, no improvement of the physical system should be
122 observed in both conditions, nor should an increase in understanding be found. By contrast, if
123 technical reasoning is important for completing partial or biased information, then an
124 improvement of the physical system should be observed in both conditions, and it should be
125 accompanied by an increase in understanding.

126 **Results and Discussion**

127 The results supported the second prediction. The wheel speed increased over
128 generations in both the Speed-Only condition [Generation estimate, 3.03 m h⁻¹; 95%
129 Confidence Interval (CI): 1.28 to 4.73] and the Configurations+Speed+Noise condition
130 (Generation estimate, 1.77 m h⁻¹; 95% CI: 0.53 to 2.96; **Fig. 2A, fig. S2**) in parallel to the
131 participants’ total understanding score (Speed-Only: Generation estimate, 2.04; 95% CI: 0.35

132 to 3.88; Configurations+Speed+Noise: Generation estimate, 1.85; 95% CI: 0.40 to 3.05; **Fig.**
133 **2B**). A link was also found in both conditions between the wheel speed (the best speed of the
134 last two trials) and the total understanding score (Speed-Only: Wheel-speed estimate, 0.55;
135 95% CI: 0.39 to 0.73; Configurations+Speed+Noise: Wheel-speed estimate, 0.65; 95% CI:
136 0.46 to 0.84; **Fig. 3B**). To examine convergence, we computed an intra-generation similarity
137 score, which reflected the similarity between the wheel configurations of the participants of
138 the same generation. We found that this intra-generation similarity score increased over
139 generations within both conditions but not between conditions (Speed-Only: Generation
140 estimate, 1.41; 95% CI: 0.72 to 2.10; Configurations+Speed+Noise: Generation estimate,
141 1.75; 95% CI: 1.25 to 2.18; Between: Generation estimate, 0.67; 95% CI: -0.14 to 1.36; **Fig.**
142 **3C**). Taken together, these results indicate that high-fidelity transmission can arise through an
143 increased understanding of the task that allow individuals to converge to optimal solutions
144 [for similar results in a Configurations+Speed condition, see (41); see also **fig. S3**].

145 A careful examination of the evolution of wheel speed over the 25 trials (**Fig. 2A**)
146 provides additional information about the dynamics of the cognitive processes involved in
147 each condition. In the Configurations+Speed+Noise condition, the participants in the second-
148 to-fifth generations maintained the wheel speed from their first trials at the same level as that
149 of the last trials of their predecessors. This pattern, which is similar to that of the
150 Configurations+Speed condition of Osieurak et al. [(41); **fig. S4**; see also (22)], suggests that
151 the participants tended to use – but also to be canalized by [(22, 41) see also (42–44)] – social
152 information to begin to form a causal representation of what could be an effective physical
153 system. The early impact of social information on the formation of this causal representation
154 is confirmed by the presence of a link between the total understanding score and the wheel
155 speed (the best speed of the first two trials; Wheel-speed estimate, 0.25; 95% CI: 0.01 to 0.45;
156 **Fig. 3A**).

157 By contrast, as shown in **Fig. 2A**, the participants in the Speed-Only condition seemed
158 to reinvent the wheel at each generation, with the participants in the second-to-fifth
159 generations obtaining a very low performance in their first trial, close to that of the first trial
160 of participants in the first generation. Nevertheless, over their five trials, the participants in
161 the second-to-fifth generations tended to improve the physical system systematically and
162 progressively, leading them to outperform their predecessors. This outcome suggests that the
163 participants in this condition benefited from the social information provided by the speed of
164 previous wheels by comparing it with the performance based on their initial causal
165 representation of the wheel system. Thus, the greater the gap between the performance of
166 their predecessor and their initial performance, the more the participants attempted to modify
167 – and thus enhance – their causal representation of the physical system, thereby allowing
168 them to improve dramatically their wheel system over their own trials. Support for this
169 interpretation comes from the absence of a link in this condition between the total
170 understanding score and the wheel speed, when the best speed of the first two trials is
171 considered (Wheel-speed estimate, 0.16; 95% CI: -0.05 to 0.36; **Fig. 3A**).

172 The inertia dimension had a greater impact on the wheel speed than the center of mass
173 dimension. Therefore, the considerable increase in wheel speed over the five trials implied
174 that the participants in the Speed-Only condition explored further the inertia dimension and
175 preferentially enhanced their understanding of this dimension. To investigate this aspect, we
176 computed two exploration scores, one for the inertia dimension and the other for the center-
177 of-mass dimension, which reflected the exploration of each dimension over the five trials. We
178 found that the inertia exploration score increased over generations in the Speed-Only
179 condition (Generation estimate, 3.63; 95% CI: 1.69 to 5.49; **Fig. 3E**) in parallel with the
180 participants' inertia understanding score (Generation estimate, 2.28; 95% CI: 0.42 to 4.13;
181 **Fig. 2D**). In broad terms, the mere availability of information about the predecessor's

182 performance was enough to orient the participants toward a technical-reasoning-based
183 exploration [reasoned trial and error (25, 45)].

184 The pattern in the Configurations+Speed+Noise condition was different, with no
185 significant effect of generations on the inertia exploration (Generation estimate, -0.81; 95%
186 CI: -2.49 to 0.81; **Fig. 3E**) and understanding scores [Generation estimate, 0.26; 95% CI: -
187 0.98 to 1.56; **Fig. 2D**; for similar results in a Configurations+Speed condition, see (41)]. By
188 contrast, there was an increase in the participants' center-of-mass understanding score
189 (Generation estimate, 1.59; 95% CI: 0.79 to 2.50; **Fig. 2C**). This increase was not found in the
190 Speed-Only condition (Generation estimate, -0.24; 95% CI: -1.18 to 0.75; **Fig. 2C**).
191 Interestingly, the increase in the center-of-mass score reported in the
192 Configurations+Speed+Noise condition was accompanied by a decrease in the center-of-mass
193 exploration score over generations (Generation estimate, -4.88; 95% CI: -8.05 to -1.53; **Fig.**
194 **3D**). The random noise added before transmission fortuitously and almost systematically led
195 to the generation of unbalanced wheel configurations (**table S1**), which was critical to observe
196 the effect of the position of the wheel's center of mass on its speed. Random noise, along with
197 the canalizing effect associated with the transmission of wheel configurations, seems to have
198 directed the participants' attention to the center-of-mass dimension, leading them to improve
199 their understanding of this dimension. These findings highlight how the introduction of
200 random modifications can favor the understanding of often poorly understood dimensions,
201 which can in turn lead to specific innovations. The presence of a decrease in the center-of-
202 mass exploration score suggests that these innovations did not result from lucky errors or
203 occasional experiments but from the direct contribution of random modifications introduced
204 along with the canalizing effect. This is telling with respect to our hypotheses because if
205 participants were using a strategy in which they introduced random modifications and
206 selected the best outcomes, (1) participants in both conditions would mostly explore the

207 center-of-mass dimension (favored by random modifications) and (2) transmission chains in
208 the two conditions would converge towards the same outcome (but see **Fig. 3C**).

209 The present study extends previous findings, which have questioned the crucial role of
210 copying mechanisms (46, 47) and/or emphasized the importance of causal
211 understanding/inductive biases (48–50) and innovative skills in CTC (51, 52). In this
212 experiment, participants with very little or randomly transformed social information managed
213 to improve and converge towards similar outcomes than participants with complete
214 information [(13, 53) see also (54, 55)]. This is remarkable and demonstrate the importance of
215 technical reasoning in producing CTC: Technical reasoning is a reconstruction mechanism
216 that allows us to recover from partial or degraded information obtained through social
217 learning and therefore guarantees the high-fidelity transmission of advantageous technologies
218 (i.e., the high similarity between the wheel configurations). Said differently, technical
219 reasoning can be viewed as a potential cognitive mediator of CTC that allows individuals to
220 filter information acquired either through their own experience (asocial learning) or through
221 social learning, by extracting relevant information and rejecting irrelevant information,
222 irrespective of the origin of this information (25). Technical reasoning might participate in
223 both the innovative component and the high-fidelity component of CTC, thus implying that
224 the distinction between these two components might be of convenience rather than of
225 cognitive distinctness.

226 The use of micro-society paradigms has provided significant insights into the origin of
227 CTC. As stressed by Miton and Charbonneau (56), participants in micro-society paradigms
228 “are adept inventors, capable of innovating in a matter of minutes” (p. 4). Consistent with this
229 fact, our participants were able to improve a multidimensional technology, which is not
230 obviously intuitive as shown by the results, as well as the understanding of it in only about 20
231 min and five trials. Showing that technical reasoning can play a reconstruction role in such

232 paradigms can also renew the question of how technologies have evolved in early hominins.
233 For instance, the Oldowan industrial complex emerged at around 2.6 million years ago. This
234 industry comprises mainly sharp-edged flakes and the cores from which they were removed
235 (57). There is no clear tradition within the Oldowan prior to 2 million years ago (58). The
236 Acheulean industry, which appeared around 1.75 million years ago, corresponds to bifacially
237 shape stone tools used as handaxes and cleavers. This industry is characterized by a striking
238 homogeneity, which persisted for around 1.5 million years (59, 60). This shift may reflect the
239 emergence of high-fidelity transmission in our lineage. Several proposals have been made for
240 interpreting this shift at a cognitive level, with a particular focus on social cognitive skills (61,
241 62). The findings reported here provide an alternative interpretation in suggesting that
242 technical reasoning could have also contributed to the emergence of high-fidelity
243 transmission. Of course, this interpretation must be taken with caution because other aspects
244 can also be fundamental to maintain the stability of technologies over long periods of time,
245 such as the – perhaps presupposed – lesser cost of copying compared to understanding the
246 technical behavior of conspecifics and the interaction of this learning cost with environmental
247 conditions (7, 63), the different social-learning strategies [e.g., prestige bias, conformity bias
248 (20, 64)], or the superiority of some social-learning conditions over others in the transmission
249 process [e.g., superiority of communication over reverse engineering (65, 66)]. Regardless,
250 our results show that CTC and the high-fidelity transmission of technology between
251 individuals should not be systematically interpreted as evidence of cognitive mechanisms
252 capable of copying coupled to the random retention of useful modifications.

253 **Materials and Methods**

254 *Ethics*

255 The Ethics Committee of the University of Lyon Department of Psychology approved the
256 study, and the procedure was carried out in accordance with the ethical standards of the 1964

257 Declaration of Helsinki. Informed consent was obtained from all participants after the nature
258 and possible consequences of the study were explained [see (41)].

259 *Participants*

260 One hundred and forty-six students at the University of Lyon took part in the study ($M_{\text{age}} =$
261 20.84 , $SD_{\text{age}} = 2.91$; 102 women). The participants were non-selectively recruited through
262 advertisements posted on social media websites [see (41)].

263 *Experimental apparatus*

264 The wheel system used in the present study was the same as the one used by Osiurak et al.
265 [(41); for an illustration, see <https://osf.io/m3d7q/>]. A description is provided in **fig. S5**.

266 *Procedure*

267 The procedure was basically the same as in (41). The experiment took place in an
268 experimental room at the University of Lyon (around 30 min in duration). The participants sat
269 at a table placed 2 m from the experimental apparatus. Before the experiment, the participants
270 completed a consent form. After the experiment, they indicated whether they had an academic
271 background in engineering or physics.

272 *Experimental design*

273 *Building phase.* This phase was similar in both conditions. Instructions were similar to those
274 of Osiurak et al. [(41); see <https://osf.io/m3d7q/>]. The participants had five trials to optimize
275 the speed of a wheel that descended a 1-m-long inclined track. They could move four weights
276 to any of 12 discrete positions along each spoke and were free to choose their own
277 configuration (from 1 to 12, with 1 being the closest position to the center of the wheel and 12
278 the furthest position from the center of the wheel). After the participants used a marker pen to
279 indicate the positions of the four weights on the wheel (i.e., a paper version of the

280 configuration), the experimenter positioned the weights on the physical wheel accordingly.
281 The participants were not allowed to move the weights on the physical wheel themselves in
282 order to prevent damage due to potential repeated awkward manipulations. The wheel also
283 needed to be placed correctly in its initial position and the release had to be accomplished
284 without any abrupt movements in order to avoid a modification of the trajectory of the wheel.
285 Nevertheless, the participants could scrutinize the experimenter moving the weights and
286 releasing the wheel as well as the wheel descending the track. The time it took the wheel to
287 travel down the track was automatically recorded by a computer program (see
288 <https://osf.io/m3d7q/>). The wheel speed and the associated configuration were then displayed
289 to the participants, who had as much time as they needed to consult their last two
290 configurations and choose the next one. As explained above, we used a paper-and-pencil
291 method to display the wheel speeds and the associated configurations (see
292 <https://osf.io/m3d7q/>). After three trials, the experimenter reminded the participants in the
293 Speed-Only condition that the wheel speeds of their last two trials would be transmitted to the
294 next participant in the chain. In the Configurations+Speed+Noise condition, the experimenter
295 reminded the participants that their last two configurations and the associated speeds would
296 be transmitted to the next participant in the chain. In this condition, a random noise was
297 introduced by the experimenter into the wheel configurations before transmission, by moving
298 the four weights six positions closer to or farther from the center of the wheel (i.e., the
299 absolute sum of the modifications equaled 6). Thus, if the configuration of the wheel of a
300 participant on their fourth trial was, for instance, [Position_{Top} Weight: 9; Position_{Front} Weight: 9;
301 Position_{Bottom} Weight: 5; Position_{Back} Weight: 5], a random modification of six positions was
302 applied (e.g., +1;-3;+2;0), which modified the configuration of the wheel (i.e., Position_{Top}
303 Weight: 9+1=10; Position_{Front} Weight: 9-3=6; Position_{Bottom} Weight: 5+2=7; Position_{Back} Weight:
304 5+0=5]. The configurations thus modified and their associated speeds were then transmitted

305 by the experimenter to the next participant. The computer program used to generate these
306 random positions is available at <https://osf.io/m3d7q/>. The introduction of this random noise
307 frequently generated wheels that did not descend (i.e., speed of 0 m h⁻¹). Sometimes, the
308 program could generate two configurations with null speed for the same participant. To
309 ensure that the participants in the second-to-fifth generations received at least one
310 configuration with a wheel that descended, we reran the program until we obtained a wheel
311 with a non-null speed for the second configuration when the speed associated with the first
312 configuration was already null. There were 28 chains of five participants each (i.e., 14 chains
313 in the Speed-Only condition and 14 chains in the Configurations+Speed+Noise).

314 *Testing phase.* In both conditions, the participants completed this phase after the building
315 phase [see (41)]. They were instructed that they would be presented with items consisting of
316 four wheels and that they would have to choose which of the four wheels would roll down the
317 rails faster in their opinion. They could take as much time as they needed to complete the test.
318 They received no feedback. All the participants saw the same items in the same order. The
319 understanding test consisted of 24 items (i.e., 12 inertia items and 12 centre of mass items).
320 The test is available at <https://osf.io/m3d7q/>. Finally, the participants had to write a brief
321 theory (i.e., less than 340 characters long) about the functioning of the wheel system, which
322 always started with “The wheel covers the distance faster when...” [for a similar procedure,
323 see (22)]. The data collected about these theories are not discussed in the present report.

324 *Statistical analyses*

325 One participant in the Speed-Only condition received an incorrect speed from the previous
326 participant because of an experimental error. The data of this participant were removed, and
327 the participant was replaced by a new participant. We checked for the presence of outliers for
328 each condition separately. As our key predictions concerned the increase in wheel speed over

329 generations, we explored whether some chains behaved differently from the others on this
330 aspect. To do so, we computed the slope associated with each chain with x being the position
331 of the participant in the chain and y the best speed of their last two trials. For each condition,
332 we obtained 14 slopes. We considered as outliers the chains with a slope that did not fall
333 within two standard deviations from the mean. This procedure led us to remove one chain of
334 five participants in the Speed-Only condition, which we replaced with a new chain of five
335 participants. No chain was removed for the Configurations+Speed+Noise condition. In total,
336 the data of six participants were excluded, giving us a final sample of 140 participants (14
337 chains of five participants for each condition).

338 Wheel speed corresponded to the best speed of the first or last two trials. Wheels that did not
339 travel down were assigned a speed of 0 m h^{-1} . To compute the intra-generation similarity
340 score, we first selected the configuration of the wheel that was fastest among the last two
341 trials of each participant. Then, for the within-condition similarity score, we compared this
342 best configuration with the 13 best configurations produced by the other participants of the
343 same generation, and we did so for each participant of each generation. The comparison was
344 based on the sum of absolute differences of the positions of the four weights between two
345 configurations. The positions varied from 1 to 12. Therefore, the maximum absolute
346 differences could be 44 [i.e., $(\text{Position}_{12} - \text{Position}_1) \times 4 \text{ weights}$]. The sum of absolute
347 differences reflected the dissimilarity between the two configurations. Therefore, we
348 subtracted this sum from 44 to obtain the similarity score. The procedure was the same for the
349 between-condition similarity score except that we compared the best configuration of each
350 participant with the 14 best configurations produced by the participants of the same
351 generation in the other condition. More detail about this intra-generation similarity score is
352 given at <https://osf.io/m3d7q/> [for a similar procedure, see (67, 68)]. The inertia exploration
353 score corresponded to the difference between the smallest and the greatest sum of positions of

354 the four weights on the five trials. The greater this difference, the greater the exploration. The
355 center-of-mass exploration score corresponded to the surface of the convex envelope that
356 contained the centers-of-mass coordinates of the five wheels. For each wheel, the coordinates
357 of its center of mass were computed by subtracting the position of the bottom weight from
358 that of the top weight (x -coordinate) and the position of the back weight from that of the front
359 weight (y -coordinate). The greater this surface, the greater the exploration. More detail about
360 these two exploration scores is provided at <https://osf.io/m3d7q/>.

361 In both conditions, we first explored the wheel speed over generations. Wheel speed
362 corresponded here to the best speed of the last two trials. Wheels that did not travel down
363 were assigned a speed of 0 m h^{-1} . We used regression modelling in R [(69); lmerTest package
364 (70)] to fit a linear model with ‘Wheel speed’ as outcome variable, ‘Generation’ as fixed
365 effect, and ‘Chain’s identity’ as random effect. The same analyses were conducted for the
366 understanding scores (Total, Center of Mass, and Inertia), the intra-generation similarity score
367 (Within-condition and Between-condition), the exploration scores (Center of Mass and
368 Inertia) and the best speed of the first two trials (Two participants in the Speed-Only
369 condition and four participants in the Configurations+Speed+Noise condition were excluded
370 from this analysis because their first two wheels did not descend). We also used regression
371 modelling in R [(69); lmerTest package (70)] to explore the links between the understanding
372 scores (Total) and the best speed of the first *or* last two trials. We fitted a linear mixed model
373 with ‘Understand Score (Total)’ as outcome variable, ‘Wheel speed (the best speed of the first
374 *or* last two trials)’ as fixed effect, and ‘Generation’ and ‘Chain’s identity’ as random effects.
375 Statistical significance was set at $p < .05$ and bootstrapping method was used to estimate 95%
376 confidence intervals.

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534 **Competing interests**

535 Authors declare that they have no competing interests.

536 **Data and materials availability**

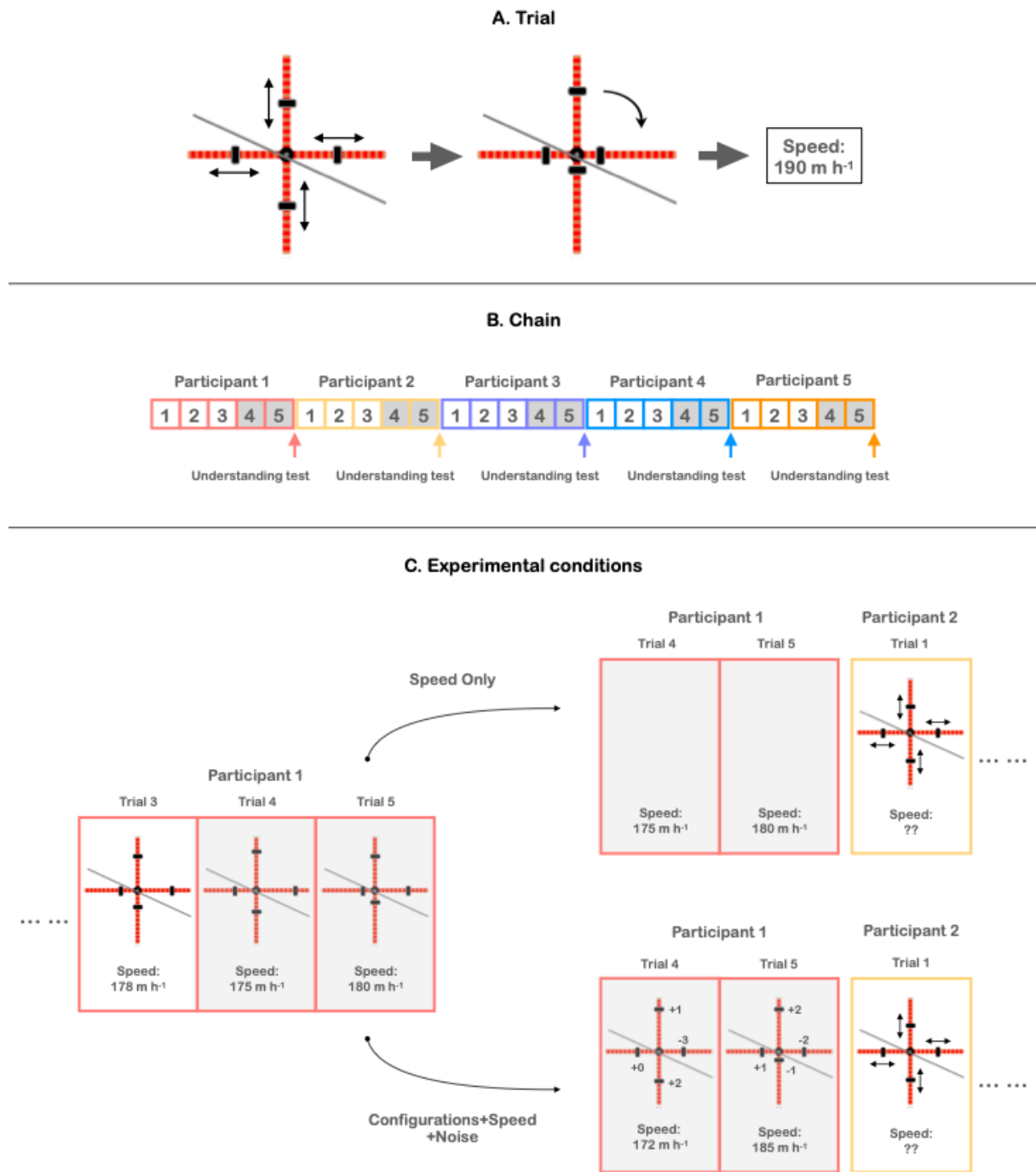
537 The data that support the findings of this study and the codes used in this study are available
538 at <https://osf.io/m3d7q/>. All data needed to evaluate the conclusions in the paper are present
539 in the paper and/or the Supplementary Materials.

540 **Supplementary Materials**

541 Figs. S1 to S5

542 Table S1

543

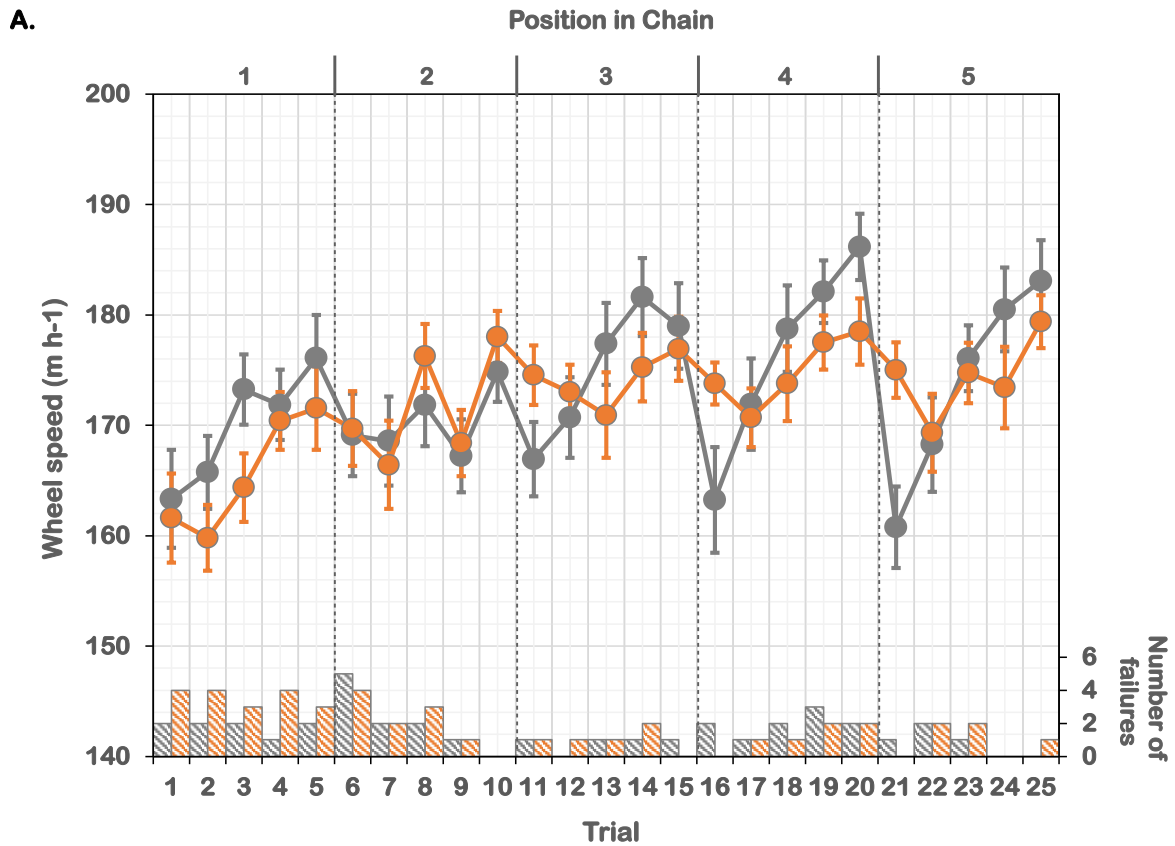


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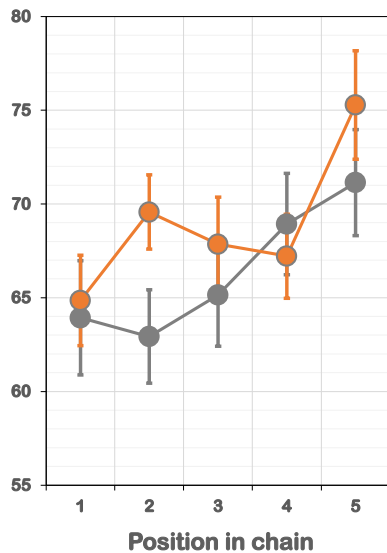
545 **Fig. 1. Experimental task and design.** **A.** The task consisted of minimizing the time it took a wheel to travel
 546 down an inclined track. The wheel had four radial spokes. On each spoke, a weight could be moved closer to or
 547 further from the center of the wheel on 12 positions. **B.** The participants performed the task as members of
 548 chains of five participants. Each of the participants had five trials to improve the wheel system by modifying the
 549 wheel configuration. The experimenter transmitted to each participant (except those of the first generation) the
 550 information about the last two trials (grey) of the previous participant. After the five trials, the participants'
 551 understanding of the wheel system was assessed with an understanding test (12 center-of-mass items and 12
 552 inertia items). **C.** In the Speed-Only condition, only the wheel speeds of the last two trials (grey) were
 553 transmitted to the next participant. In the Configurations+Speed+Noise condition, the participants were given

554 two weight configurations and their associated speeds. The configurations came from the previous participant in
555 the chain but were modified by randomly moving the four weights six positions closer to or farther from the
556 center of the wheel.

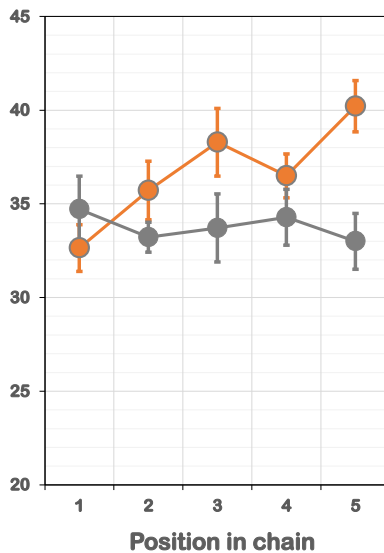
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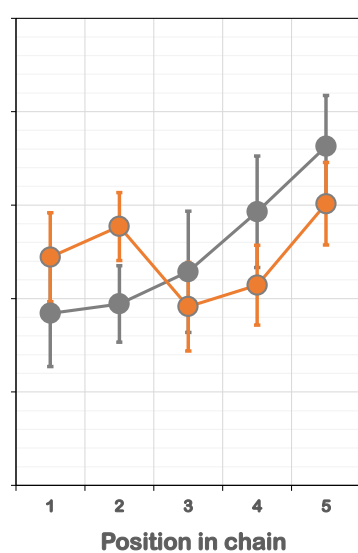
B. Understanding (Total)



C. Understanding (Center of mass)



D. Understanding (Inertia)



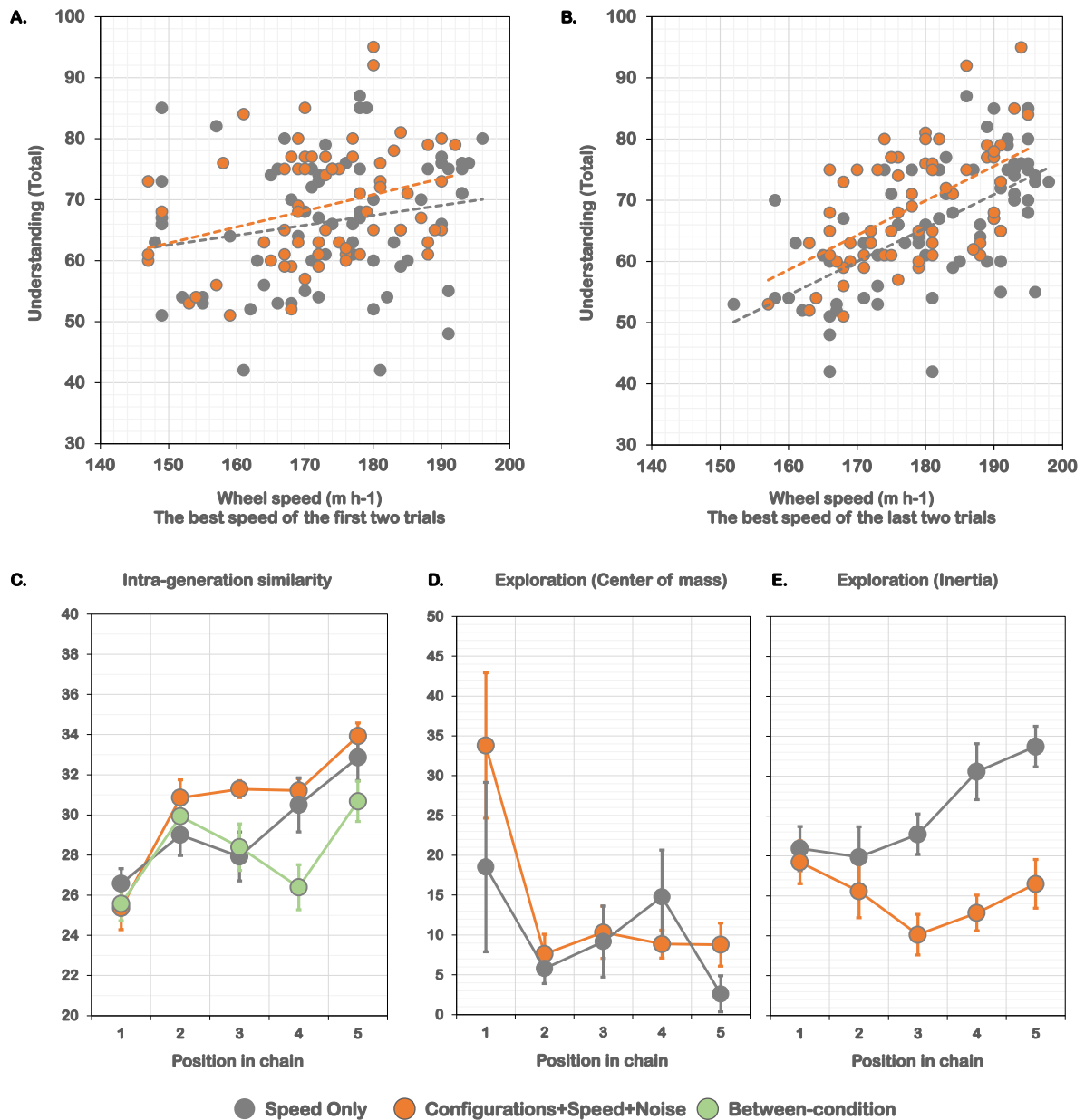
● Speed Only ● Configurations+Speed+Noise

558

559 **Fig. 2. Parallel improvement of the wheel system and of its understanding.** A. Wheel speed over generations
 560 for non-failure wheels and number of failures in the Speed-Only condition (grey) and in the
 561 Configurations+Speed+Noise condition (orange). B-D. Understanding scores over generations (B: Total; C:

562 Center-of-mass items only; D: Inertia items only). The performance obtained by a control group is also shown
563 [see (41); Mean: Yellow; Standard Error: Blue]. Error bars indicate standard errors.

564



565

566 **Fig. 3. Links between the wheel speed and the understanding scores and increase of intra-generation**
 567 **similarity and exploration scores over generations. A-B.** Links between the wheel speed (A: The best speed
 568 of the first two trials; B: The best speed of the last two trials) and the understanding scores (Total). **C.** Intra-
 569 generation similarity scores over generations (Within-condition: Speed-Only condition, Grey;
 570 Configurations+Speed+Noise condition, Orange; Between-condition: Green). **D-E.** Exploration scores (D:
 571 Center of mass; E: Inertia) over generations. Error bars indicate standard errors.