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1           **To draw or not to draw: understanding the temporal organization of**  
2                                   **drawing behaviour using fractal analyses**

3

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26 **Abstract**

27 Studies on drawing often focused on spatial aspects of the finished products. Here, the  
28 drawing behaviour was studied by analysing its intermittent process, between *drawing* (i.e.  
29 marking a surface) and *interruption* (i.e. a pause in the marking gesture). To assess how this  
30 intermittence develops with age, we collected finger-drawings on a touchscreen by 185  
31 individuals (children and adults). We measured the temporal structure of each drawing  
32 sequence to determine its complexity. To do this, we applied temporal fractal estimators to  
33 each drawing time series before combining them in a Principal Component Analysis  
34 procedure. The youngest children (3 years-old) drew in a more stereotypical way with long-  
35 range dependence detected in their alternations between states. Among older children and  
36 adults, the complexity of drawing sequences increased showing a less predictable behaviour  
37 as their drawings become more detailed and figurative. This study improves our  
38 understanding of the temporal aspects of drawing behaviour, and contributes to an objective  
39 understanding of its ontogeny.

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42 Keywords: temporal complexity, drawing intermittence, marking gesture, anthropology,  
43 evolution, mathematics, *Homo sapiens*

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## 52 **1. Introduction**

53           The expression of artistic behaviour is predominant in *Homo sapiens*, even if the time  
54 allocated to such activities tends to decrease with age. A good example of such declining  
55 interest across the lifetime can be seen in drawing. Prevalent among children, drawing persists  
56 as a recreational activity only among a minority of adults, and as a professional activity  
57 among a select few. Drawing develops from internal representativeness (i.e. a drawing  
58 representative only from the perspective of the child who produces the drawing) to external  
59 representativeness (i.e. a drawing interpretable from the perspective of an independent  
60 observer) around the age of 3-4 years (Freeman, 1993; Martinet et al., 2021). Drawing  
61 behaviour has been studied in different research fields, especially in psychology, e.g. to  
62 characterise its ontogeny (Luquet, 1927; Willats, 2005), its representational development  
63 (Adi-Japha et al., 1998; Cherney et al., 2006), the use of colour (Wright and Black, 2013), the  
64 comprehension of realism (Jolley et al., 2000) or the influence and role of gender (Cherney et  
65 al., 2006; Turgeon, 2008). Such studies have provided critical information about drawing  
66 behaviour, despite the fact that the analyses used are often qualitative and subject to biases.

67           Adi-Japha et al (1998) showed that young children, even if not capable of attributing  
68 meanings to the entirety of their drawing, can make sense of broken lines which seem to be  
69 more descriptive than curved ones. Although relevant, this method remains subjective  
70 because researchers directly question children about what their drawings represent. Moreover,  
71 very young children (toddlers) are unable to express themselves with respect to their  
72 drawings. Furthermore, the majority of drawing studies focus on spatial measures, whereas  
73 the temporal aspects that might also be important in revealing cognitive and decision-making  
74 processes remain underexplored. Recent developments in mathematical analyses in animal  
75 behaviour might bring new perspectives to the study of such processes.

76           Indeed, new analytical approaches from statistical physics are now being developed to  
77 study individual behaviour, such as fractal analyses. An object is considered fractal when any  
78 of its parts examined separately resemble its overall structure at any magnification scale,  
79 either in the spatial or temporal domain (Mandelbrot, 1977). A good example of a natural  
80 fractal object is Romanesco broccoli, but many other natural systems have fractal structure in  
81 the spatial domain, such as river networks (Rinaldo et al., 1993) and human lung architecture  
82 (Nelson et al., 1990). Fractal structure is also found in the temporal domain, in processes such  
83 as human breathing cycle dynamics (Peng et al., 2002) or human sleep EEG (Weiss et al.,  
84 2009). In the behavioural sciences, recent studies have established that fractal analyses of  
85 spatial and temporal patterns can lead to a better understanding of animal and human  
86 behaviour (MacIntosh, 2014; Rutherford et al., 2003).

87           On one hand, the study of movement behaviour through spatial fractal analyses have  
88 allowed comparisons between observed movement patterns and theoretically optimal foraging  
89 patterns (Sims et al., 2008; Viswanathan et al., 1999). We previously applied this approach in  
90 examining the efficiency of the drawing trajectory, defined as the correct reading of the  
91 drawing with minimal detail in chimpanzees (*Pan troglodytes*) and humans (*Homo sapiens*).  
92 Analogous to the trajectory of an animal in its environment, we wanted to know if the  
93 efficiency of drawings made on a screen differed between humans and chimpanzees, and with  
94 age in humans. Results show that the drawing spatial index was lowest in chimpanzees,  
95 increased and reached its maximum between 5-year-old and 10-year-old children, and  
96 decreased in adults, whose drawing efficiency was reduced by the addition of details  
97 (Martinet et al., 2021).

98           On the other hand, temporal fractal analyses have shown that an animal's  
99 physiological condition (e.g. health status or degree of physiological stress) affects its  
100 sequences of behaviour (Alados, 1996). The concept of fractal time reflects the degree to

101 which current behavioural states depend not only on states immediately preceding them in the  
102 sequence but also on those that occur much earlier in the sequence (so-called long-memory  
103 processes) (Delignières et al., 2005). Like spatial fractal analyses, temporal fractal analyses  
104 also suggest an optimal structure in behaviour time series, within which a normally  
105 functioning individual should fall (MacIntosh, 2014). Some environmental pressures or  
106 physiological impairments can lead to a loss of complexity in the behavioural sequences of an  
107 individual, associated with increases in periodicity or long-range dependence (i.e. greater  
108 stereotypy) (MacIntosh et al., 2011; Maria et al., 2004; Meyer et al., 2020). Other factors may  
109 in contrast lead to increased complexity, i.e. reduced long-range dependence and increased  
110 behavioural stochasticity (Rutherford et al., 2003). To summarise or simplify the concept,  
111 certain complexity signatures in behaviour sequences equate to increased stability and/or  
112 adaptability, which is the case for some physiological processes as well as sequences of  
113 animal behaviour, where it can be an indicator of well-being (Alados, 1996; Maria et al.,  
114 2004). By allowing more detailed insight into behavioural sequences, temporal fractal  
115 analyses open up new research perspectives for diverse fields of study.

116 In humans, behavioural sequences are complex and structured in time by multiple  
117 factors (e.g., environmental, psychological, physiological), which may limit randomness in  
118 the occurrence of behaviour. Several behaviours have been described as fractal, such as  
119 patterns of physical activity (Paraschiv-Ionescu et al., 2008) or short-message communication  
120 in online communities (Rybski et al., 2009). Considering drawing and handwriting, both  
121 pacing and grip force showed a fractal dimension (Fernandes and Chau, 2008). However, the  
122 latter study was restricted to an analysis of young adults drawing circles in synchrony with a  
123 metronome, so these results cannot be generalised.

124 In the present study, we sought to improve our understanding of drawing behaviour  
125 and its ontogenetic processes by applying temporal fractal analyses to drawing data from

126 humans of all ages. Drawing behaviour is an intermittent process, composed of two main  
127 states, including *drawing* (i.e. marking a surface) and *interruption* (i.e. a break in the marking  
128 gesture). The temporal structure of each drawing sequence (i.e. sequence memory) can be  
129 measured to determine its degree of complexity (MacIntosh et al., 2011). To assess how  
130 drawing intermittence develops with age, we collected drawings from 185 individuals of  
131 different ages, including children as well as both naive and expert adults. We hypothesized  
132 that drawing sequences would be simpler in young children (aged 3 to 5 years), with greater  
133 periodicity and long-range dependence in their alternations between states. Indeed, young  
134 children who have not yet entered the representative phase of drawing may be more interested  
135 in gestures and engaged more in play than in drawing. On the contrary, complexity in drawing  
136 sequences may increase among older children and adults, for whom drawings become more  
137 and more detailed and representative.

138 To accomplish our aims, we applied multiple temporal fractal estimators to study  
139 long-memory processes in drawing time series. A first challenge was to link these few  
140 estimators to drawing behaviour, as we are not aware of any previous studies on this topic. A  
141 second challenge was to assess the effectiveness of these fractal estimators, as there is little  
142 consensus as to which are most appropriate for a given set of data (Stadnitski, 2012; Stroe-  
143 Kunold et al., 2009). Therefore, we first present a robust analytical approach to performing  
144 these fractal analyses using our drawing dataset to decrease errors and biases. We then  
145 introduce the analysis of complementary indices such as the duration of drawing behaviour in  
146 relation to the duration of the drawing session, and the number of swings between drawing  
147 and non-drawing states during the drawing session. We discuss our results in the light of  
148 biological processes.

149

## 150 **2. Material and methods**

151 2.1 Ethics

152 We followed the ethical guidelines of our research institutions and obtained ethical  
153 approval from the University of Strasbourg Research Ethics Committee (Unistra/CER/2019-  
154 11). Drawings were anonymously collected. The contribution of all participants was voluntary  
155 and subject to parental consent for children.

156

157 2.2 Participants

158 One hundred and forty-four children (67 girls and 77 boys) and forty-one adults (21 women  
159 and 20 men) participated in this study (Table 1). We worked with children from kindergarten  
160 and primary school in Strasbourg, France. We collected their drawings over two consecutive  
161 years (in 2018 for kindergarten children and in 2019 for primary school children). For this  
162 reason, 6-year-old children could not be tested in 2019 since they had already participated in  
163 the study the year before. Adult participants were between 21 and 60 years old. In addition to a  
164 general age effect, we also tested the effect of experience in our adult participants. Among  
165 researchers and students at the authors' research institute, twenty were considered naive (naive  
166 adults:  $30.8 \pm 10.54$  years old) as they had never taken drawing lessons and did not draw as a  
167 hobby. The other twenty adults were classified as experts and included art school students and  
168 professional illustrators (expert adults:  $30.4 \pm 11.12$  years old).

169

170 **Table 1.** Groups and gender of human participants.

| Participants groups |             | Gender | Number of participants |
|---------------------|-------------|--------|------------------------|
|                     | 3-year-olds | girls  | n=5                    |
|                     |             | boys   | n=15                   |
|                     | 4-year-olds | girls  | n=10                   |
|                     |             | boys   | n=10                   |



|          |              |       |       |      |
|----------|--------------|-------|-------|------|
| Children | 5-year-olds  | girls | n=10  |      |
|          |              | boys  | n=10  |      |
|          | 7-year-olds  | girls | n=12  |      |
|          |              | boys  | n=11  |      |
|          | 8-year-olds  | girls | n=9   |      |
|          |              | boys  | n=9   |      |
|          | 9-year-olds  | girls | n=10  |      |
|          |              | boys  | n=11  |      |
|          | 10-year-olds | girls | n=11  |      |
|          |              | boys  | n=11  |      |
|          | Adults       | naive | women | n=11 |
|          |              |       | men   | n=10 |
| expert   |              | women | n=10  |      |
|          |              | men   | n=10  |      |

171

## 172 2.3 Experimental design

### 173 *2.3.1. Habituation phase*

174 Children and adults were invited to try the device, a touchscreen tablet (iPad Pro, 13-  
175 Inch, version 11.2.2) by drawing on it with their fingers. Participants could use 10 different  
176 colours displayed on the bottom of the screen and selected one of them by clicking on it.

177 Adults were tested immediately after habituation but, to avoid overstimulation, children were  
178 habituated the day before their respective tests.

179

### 180 *2.3.2. Testing phase*

181 Children were tested individually at school, either in their own classrooms (for 3-year-  
182 olds) or in the staffroom (for older children). During the test, the experimenter (LM or MP)

183 stayed with the child but kept their distance so as not to influence their behaviour. Adults  
184 participated individually, either alone in a room at the research institute (for naive subjects) or  
185 at the art school (for experts). We used a video camera to record the hand movements of each  
186 participant while drawing, in case we needed to control for any contextual issues arising  
187 during the session (e.g. disruption of the drawing session, unintentional points or lines made  
188 by the experimenter at the end of the session, *etc.*). No time limits were imposed during the  
189 study.

190 Participants were tested under two conditions to assess potential differences between a  
191 non-specific task (*free* drawing) and a specific task (drawing a *self-portrait*). Under the *free*  
192 *condition*, subjects were asked to draw whatever they wanted, with no further instructions.  
193 Under the *self-portrait condition*, subjects were asked to draw themselves. In each participant  
194 category, we randomly assigned subjects such that half began the test with the *free condition*  
195 instructions while the other half began with the *self-portrait condition*. To avoid  
196 overstimulation and a lack of concentration, none of the children participated in both  
197 conditions on the same day.

198

### 199 2.3.3. Data collection

200 Three hundred and sixty-nine drawings were collected (one drawing by a naive adult  
201 was deleted by mistake). Since there were no imposed time limits, so as to not constrain the  
202 creativity of each participant, the drawing duration was different for each person and ranged  
203 from 17 seconds to 923 seconds (mean  $\pm$  s.d. =  $250.5 \pm 189.2$ ). When the individual was  
204 drawing, a triplet  $(x, y, t)$  was recorded every 17 milliseconds on average (resolution of point  
205 recording), where  $(x, y)$  is the position of the finger on the touchscreen and  $t$  the time. For two  
206 consecutive points  $(x_i, y_i, t_i)$  and  $(x_{i+1}, y_{i+1}, t_{i+1})$ , the time interval in milliseconds is  $t_{i+1} - t_i$ . If  $t_{i+1} -$   
207  $t_i < 100$ , we considered it drawing time. If  $t_{i+1} - t_i > 100$ , we considered it non-drawing time;

208 i.e., the individual must raise their finger long enough for this stop to be voluntary (Tanaka et  
209 al., 2003). This succession of time intervals was then transformed into a binary series of -1  
210 (not drawing) and 1 (drawing), where the duration between two consecutive points was set at  
211 1 millisecond. Note that analyses with other resolutions (10 milliseconds and 17 milliseconds)  
212 were performed for comparison and gave similar results (see Supplementary Materials Figure  
213 1). The resultant time series can be represented as a barcode as shown in Figure 1. The width  
214 of each black band corresponds to a drawing duration, while a non-drawing duration is  
215 equivalent to the width of a white band. Each video was watched several times to remove  
216 moments during which participants were distracted by something else (Longstaff and Heath,  
217 1999) (simulations showed that this did not mathematically impact the results, see  
218 Supplementary Materials Box1) . This happened a few times at school during drawing  
219 sessions with children. This concerns only 22 drawings in our final analyses (i.e. 6.4% of the  
220 dataset) where 1 to maximum 2 durations were removed, representing  $12.2 \pm 7.1\%$  of the final  
221 sequence (these were generally times exceeding 15 seconds on average and caused by a child  
222 entering the room, the bell for recess ringing, *etc*).

223

224

225

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227

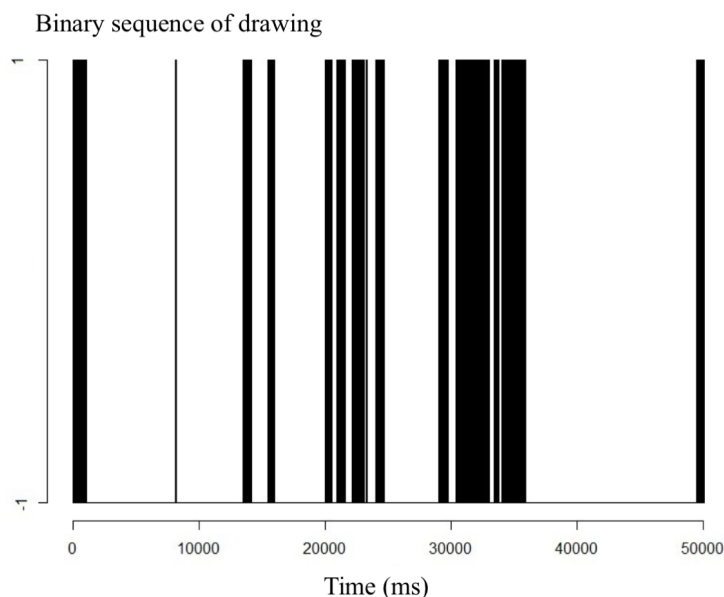
228

229

230

231

232



233 **Figure 1.** Example of a binary sequence of intermittent drawing, denoted 1 for drawing and -1  
234 for non-drawing behaviour. Black bars reflect the durations of the drawing state while white  
235 bars reflect the durations of the non-drawing state.

236

## 237 2.4 Analyses

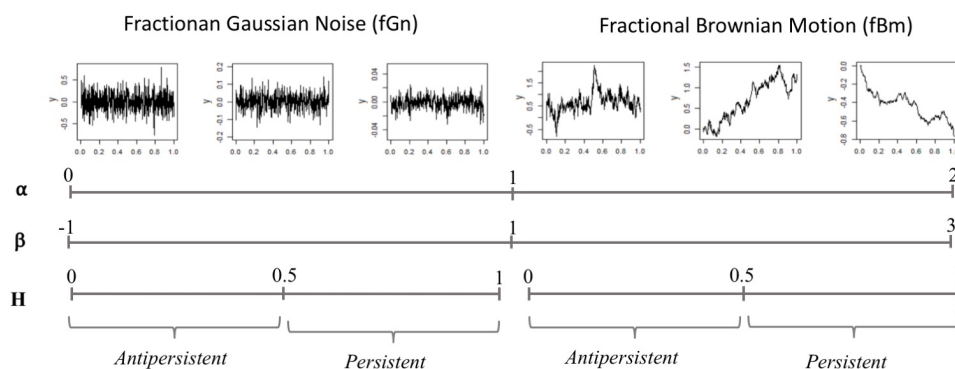
### 238 2.4.1. Type of signal

239 Fractal characteristics or long memory processes can be measured via different  
240 algorithms, each having its own statistical parameter. Here, the difficulty arises from the fact  
241 that, for each parameter, numerous estimators have been defined, but the effectiveness of each  
242 is still debated in the literature (Stadnitski, 2012; Stadnytska et al., 2010). Studies often focus  
243 on one or few estimators without a rigorous reason for comparing them. As a consequence,  
244 there is no simple and systematic way to estimate the fractal process, which often results in  
245 errors or misleading conclusions (Karagiannis et al., 2006).

246 The most widespread way to assess and quantify long memory processes in temporal  
247 sequences is estimation of the Hurst exponent ( $H$ ). This exponent is a measure of the  
248 correlation among signal components in a time series (Cannon et al., 1997; Stroe-Kunold et  
249 al., 2009) Within this framework, behavioural sequences can reflect three mutually-exclusive  
250 scenarios: (1) *persistence* ( $H > 0.5$ ) occurs when positive long-range autocorrelation exists,  
251 such that blocks of certain behaviours (e.g. drawing) are likely to be followed by blocks of  
252 similar duration in succession; (2) *anti-persistence* ( $H < 0.5$ ) occurs when negative long-range  
253 autocorrelation exists, such that blocks of behaviour are likely to be followed by blocks of  
254 divergent duration; (3) *white noise* ( $H = 0.5$ ) occurs when no sequence memory exists, i.e., the  
255 sequence is random or contains only short-range autocorrelation (Delignières et al., 2005).

256 Methods for  $H$  estimation differ depending on the signal class of the original sequence,  
257 which can be either *Fractional Gaussian noise* (fGn) or *fractional Brownian motion* (fBm)

258 (Mandelbrot and Van Ness, 1968). fGn is stationary with constant variance and mean whereas  
 259 fBm is nonstationary, even if both signals are theoretically linked: differencing fBm produces  
 260 fGn and integrating fGn creates fBm (Stadnytska et al., 2010). The same original sequence  
 261 expressed as one or the other signal class will be characterized by the same Hurst exponent  
 262 (Figure 2). However, before estimating a behaviour sequence's  $H$  exponent, it is essential to  
 263 first define its signal class, which can be done through different methods (Cannon et al.,  
 264 1997). The so-called 'temporal' methods are those which do not require prior transformation  
 265 of the data and identify statistical dependence in elements of the time series (Eke et al., 2002).  
 266 Frequency-based methods, on the other hand, are based on transformation of the time series,  
 267 for example by considering the periodogram (i.e. the spectral density of a signal). In this  
 268 article both types of methods are used with the aim of comparison and to combine the  
 269 different approaches for a more robust investigation.  
 270



271 **Figure 2.** Illustration of the fGn/fBm continuum. Values of the scaling exponent  $\alpha$  (from  
 272 detrended fluctuation analysis: DFA) and the index  $\beta$  (from power spectral analysis) are  
 273 depicted in relation to the Hurst exponent,  $H$ . This representation is largely inspired by  
 274 (Marmelat et al., 2012).

275

276 *2.4.2. Temporal methods*

277 Detrended Fluctuation Analysis (DFA)

278 To investigate long-memory processes in the sequential distribution of drawing and  
279 non-drawing durations, we employed Detrended Fluctuation Analysis (DFA) (Peng et al.,  
280 1995) which is among the most used to study binary sequences of animal behaviour  
281 (MacIntosh et al., 2013; Meyer et al., 2020; Rutherford et al., 2003). It is also a robust  
282 estimator of the Hurst exponent (Cannon et al., 1997; Eke et al., 2002). DFA calculates a  
283 scaling exponent ( $\alpha_{\text{DFA}}$ ) corresponding to the slope of the line on a log-log plot of the average  
284 fluctuation at each box size (given by the three steps, from equation 1 to equation 3 below). A  
285 lower  $\alpha_{\text{DFA}}$  reflects greater stochasticity and reduced long range memory (Figure 2) (Meyer et  
286 al., 2017). If a linear relation exists, it indicates the presence of scale invariance.

287

288 To summarize the application of DFA to our data, a binary sequence of a drawing (Figure 3a)  
289 is cumulatively summed such that

290 
$$y(t) = \sum_{i=1}^t x(i) \quad (1)$$

291 Where  $y(t)$  is the cumulative sum and  $x(i)$  is the binary sequence at each time step (1ms  
292 intervals).

293 The cumulative sum is then divided into non-overlapping boxes of length  $n$  (Figure 3a) and a  
294 least-squares regression line is fit to each box  $y_n(t)$  to remove local trend and it is repeated  
295 over all box sizes, then the fluctuation is calculated as follows (Figure 3b)

296

297 
$$F(n) = \sqrt{1/N \sum_{i=1}^N (y_n(t) - \hat{y}_n(t))^2} \quad (2)$$

298

299 Where  $\hat{y}_n(t)$  is the regression estimate for  $y_n(t)$  at each box size  $n$  and  $F(n)$  is the fluctuation  
300 of the modified root-mean-square equation across all scales available ( $2^2, 2^3, 2^4 \dots 2^m$ ) where

301  $m$  is the largest scale examined, such as  $2^m < N/2$  (rounded down to the nearest whole number)  
302 (Constantine and Percival, 2007; Stadnytska et al., 2010; Stroe-Kunold et al., 2009). We then  
303 obtained the following relationship

304  $F(n) \sim n^\alpha$  (3)

305 This method makes it possible to know whether the starting signal is a fBm or a fGn,  
306 since it can be used on both (Seuront, 2009; Stadnytska et al., 2010; Stroe-Kunold et al.,  
307 2009). The  $\alpha$  exponent can be interpreted as follows:

308

309 If  $\alpha_{DFA} > 1$ , the original signal is of the signal class fBm and  $H = \alpha_{DFA} - 1$

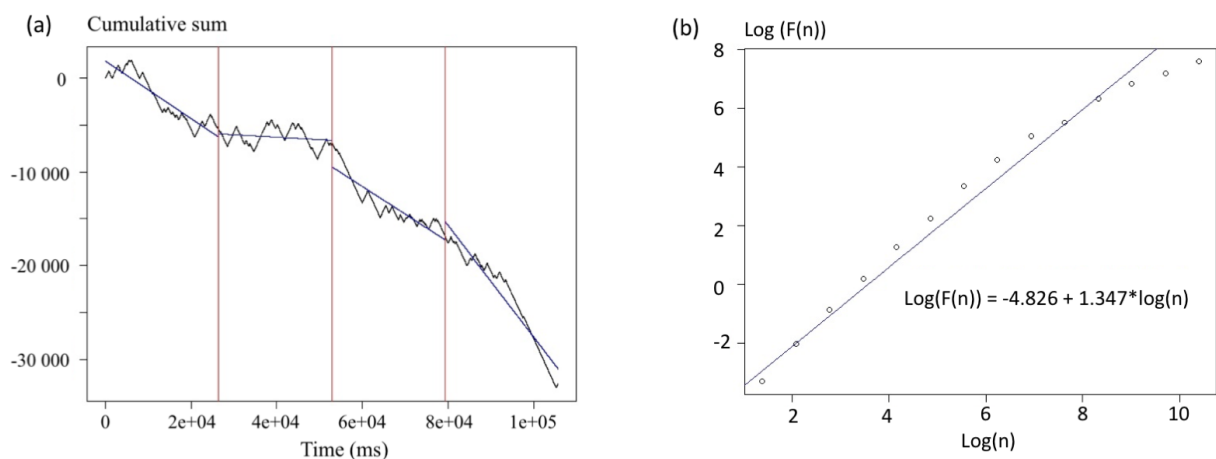
310 If  $\alpha_{DFA} < 1$ , the original signal is of the signal class fGn and  $H = \alpha_{DFA}$

311

312  $\alpha_{DFA}$  in the range of 0.5–1 and 1.5–2 reflects persistence while  $\alpha_{DFA}$  in the range of 0–0.5 and

313 1–1.5 reflects anti-persistence for fGn and fBm, respectively (Figure 2). Values of 0.5 and 1.5

314 reflect Gaussian (white) noise and Brownian motion, respectively.



315 **Figure 3.** (a) Integration of a drawing sequence. Vertical lines give an example of dividing the  
316 sequence into  $N/n = 4$  boxes. Lines in each box correspond to the polynomial regression. (b)

317 Bi-logarithmic plot of the statistic  $F(n)$  against the length of the time intervals  $n$ . The regression  
318 line allows calculation of the scaling exponent  $\alpha$ , which is its slope (1.347 in this case).

319

### 320 Hurst Absolute Value (HAV)

321 The HAV method is similar to DFA but does not integrate the time series before analyses so  
322 that  $H$  is calculated from the original binary sequences of drawing and non-drawing durations.

323 We included the HAV method because it is able to capture the self-similarity parameter in  
324 time series data where DFA fails to do so (Mercik et al., 2003). This method only works on

325 fGn, so any application of HAV on fBm signals must use their increments (i.e. the

326 corresponding fGn). A time series of class fGn of length  $N$  is divided into smaller boxes of

327 length  $n$ , denoted as  $x^{(n)}$ , and the first absolute moment is obtained as follows:

328

$$329 \delta^{(n)} = 1/(N/n) \sum_{k=1}^{N/n} |x^{(n)}(k) - \bar{x}| \quad (4)$$

330

331 This is reiterated for the different window size  $n$  with the variance  $\delta$  varying as follows:

$$332 \delta^{(n)} = n^{H_{AV}-1} \quad (5)$$

333

334 Where  $H_{AV}$  is the scaling exponent.

335

### 336 Scaled Windowed Variance (SWV)

337 Since we only had fBm series, the SWV method was selected as it a good estimator

338 for this type of signal (Delignieres et al., 2006). The fBm series  $x(t)$  is divided into non-

339 overlapping boxes of length  $n$ . In each box, a bridge detrending method is used to remove the

340 trend, this is what is recommended for series of more than  $2^{12}$  points (Cannon et al., 1997),

341 which is our case here. Then the standard deviation (SD) is calculated in each box such that



342

343 
$$SD(i) = \sqrt{\sum_{t=1}^n [x(t) - \bar{x}_i]^2 / n - 1} \quad (6)$$

344

345 With  $\bar{x}_i$  being the average in the box  $i$ . Then, the average standard deviation ( $\overline{SD}$ ) of

346 all boxes of length  $n$  is calculated such that

347 
$$\overline{SD(n)} = 1/m \sum_{i=1}^m SD(i) \quad (7)$$

348 Where  $m$  is the number of boxes of length  $n$ .

349 This step is then repeated over all possible box lengths and  $\overline{SD(n)}$  is related to  $n$  by a

350 power law

351 
$$\overline{SD(n)} \propto n^{H_{swv}} \quad (8)$$

352 The log ( $\overline{SD(n)}$ ) is plotted against log( $n$ ) and the slope of the regression is the

353 estimated Hurst coefficient  $H_{swv}$  (Cannon et al., 1997; Delignières et al., 2005).

354

### 355 *2.4.3. Frequency-based method*

#### 356 Power Spectral Density analyses (PSD)

357 Like DFA, this method is widely used to determine the signal class of time series data.

358 It is included here for comparison, because of the widespread use of PSD in standard time

359 series analysis, and the added diversity it affords us as an index based on frequency. In the

360 frequency domain, the fractal character is expressed through the following power law:

361 
$$E(f) \propto 1^{-\beta} / f \quad (9)$$

362 where  $E(f)$  is the squared amplitude for the corresponding  $f$  frequency. The  $\beta$  exponent is

363 obtained by calculating the negative slope ( $-\beta$ ) of the regression between  $\log(E(f))$  and  $\log(f)$

364 (Figure 4).  $\beta$  values range between -1 and 3, with  $\beta$  between -1 and 1 reflecting fGn and  $\beta$   
365 between 1 and 3 reflecting fBm (Delignières et al., 2005; Eke et al., 2000).  $\beta$  is linked to  $H$   
366 such that:

$$367 \quad H = (\beta + 1)/2 \text{ for fGn}$$

$$368 \quad H = \beta - 1/2 \text{ for fBm}$$

369 In the present study, the high frequencies ( $1/8 < f < 1/2$ ) are excluded. This method provides  
370 more reliable estimates of  $\beta$  and is known as <sup>low</sup>PSD (Stadnitski, 2012).

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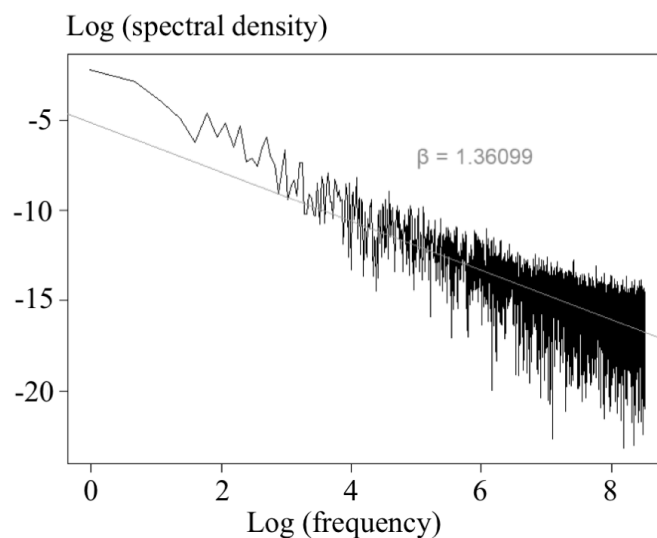
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379 **Figure 4.** Bi-logarithmic power spectrum of a time series with regression slope fitted to  
380 obtain the  $\beta$  index.

381

#### 382 *2.4.4 Methods implementation*

383 We performed DFA using the package *fractal* (Constantine and Percival, 2007) in R.  
384 For the Power Spectral Density, we based our analyses on the script found in Stadnitski et al.  
385 (2012). As the Scaled Windowed Variance and Hurst Absolute Value methods are not  
386 currently implemented in R, we coded and tested our own algorithms through Monte-Carlo  
387 simulation. We simulated, using the *somebm* package (Huang, 2013), fBm of different lengths  
388 and known  $H$ . In these simulations, the lengths of the series were defined as powers of 2, from

389  $2^{11}$ (= 2,048 points) to  $2^{15}$  (= 32,768 points). For each possible length, 100 fBm were  
390 generated with  $H = 0.2$ ,  $H = 0.4$ ,  $H = 0.6$  and  $H = 0.8$ . More than 2000 series were generated  
391 in total and the errors,  $H - \hat{H}$ , are shown in the Supplementary Materials (Figures 2 and 3).  
392 The drawing sequences obtained in this study were much longer (mean  $\pm$  s.d. =  
393 240,832ms $\pm$ 185,561ms) than these simulated series and therefore will not be a limiting factor  
394 in the estimates. Since the HAV method only works on fGn, the simulated series used are  
395 those of the respective fBm increments. These simulations have shown that the larger the size  
396 of the series, the closer the errors are to 0, proving the efficiency of these analyses.

397

#### 398 *2.4.5 H estimation*

399 The Hurst coefficient  $H$  was estimated using the four methods described above. The  
400 binary time series studied all being fBm, it was necessary to consider series consisting of the  
401 increments of these fBm (i.e. the corresponding fGn) to be able to apply certain methods such  
402 as HAV. As mentioned earlier, each of these methods does not always directly estimate the  
403 Hurst coefficient,  $H$ , but the latter's relationship with the calculated exponent is relatively  
404 simple (Figure 2). Once the four methods were applied to each series, a Pearson correlation  
405 matrix was calculated.

406

#### 407 *2.4.6 Additional temporal indices*

408 Both of the indices described below were extracted from the complete binary  
409 sequences.

410

#### 411 Proportion of drawing in the sequence

412 We first calculated the number of 1's in the sequence. Since each binary sequence had  
413 a different length, we divided the sum of 1 by the total sequence length to come up with a  
414 drawing proportion for comparison across sequences.

415

#### 416 Rate of state changes

417 The number of state changes corresponds to the number of times a participant changed  
418 their behaviour between drawing and interruption during the drawing session. For each  
419 sequence, the number of state changes was divided by the total sequence length and  
420 multiplied by 1000 to obtain a rate of change per second.

421

#### 422 *2.4.7 Statistical analysis*

423 Statistical analyses were conducted in R (version 3.6.2). Since we used four methods  
424 to estimate  $H$ , we obtained 4 estimated values of this index for each time series to use in our  
425 statistical analyses. Some previous studies have advised averaging the different estimates, but  
426 the choice of which to use and the overall number of estimators used has varied (Eke et al.,  
427 2000; Seuront, 2009). The four estimates of  $H$  were found to be highly correlated with each  
428 other. Considering that averaging variables whose variance may be different can remove  
429 information, we chose to perform a PCA. In our case, the method was used to reduce the  
430 number of estimators used into one that retained as much of the information as possible. The  
431 new resultant variable was thus constructed as a linear combination of the original variables,  
432 allowing for a synthesis of our variables into a single index (Berni et al., 2011). After using  
433 the Kaiser-Guttman criterion to select the number of axes, only values of the first principal  
434 component from the PCA – a proxy for the Hurst exponent that we term the '*Hurst axis*' –  
435 were used and set as a response variable in our statistical models. In our case, results obtained  
436 following this methodology with those resulting from averaging the estimates were equivalent

437 (see Results). We decided to retain the PCA, as it makes it possible to create a new variable  
438 (i.e. an index) which is an optimally weighted combination of correlated estimators of  $H$ .

439 A correlation of -0.43 was observed between the sequence length and the Hurst axis.  
440 Indeed, there were considerable differences in the lengths of our drawing sequences, which  
441 averaged approximately 4 minutes and ranged between approximately 17 seconds and 15  
442 minutes (mean  $\pm$  s.d. =240832 $\pm$ 185561ms; range=16848-908250ms). We were not interested  
443 in this correlation but needed to account for it when testing relationships between  $H$  and our  
444 other variables of interest, such as the *gender*, the *group* (age) or the *condition* under which  
445 the drawing was made. For this reason, the four estimated coefficients of  $H$  were recalculated  
446 on the first 50,000 points (i.e. the first 50 seconds of the drawing), 100,000 points, 150,000  
447 points and 200,000 points. DFA coefficients based on the first 50,000 points in the sequence  
448 were correlated with those based on these other three lengths (Supplementary materials,  
449 Figure 4), as well as with those from the whole sequence at more than 54%, meaning that the  
450 information contained in the first 50,000 points is a good threshold compared to that  
451 contained in the entire sequence. Therefore, we analysed only the first 50,000 points of each  
452 sequence and excluded all sequences less than 50,000 points in length (6.5% of the drawings  
453 collected).

454 Given the above criteria, we analysed 346 drawings out of the initial 369 we obtained.  
455 After recalculating the indices on the first 50,000 points for each sequence, the PCA  
456 procedure was redone. We then determined whether *group*, *gender* or *condition* were  
457 associated with variation of the “Hurst axis” by constructing a Generalized Linear Mixed  
458 Model with Gaussian error structure (*nlme* package (Pinheiro et al., 2006)). Since each  
459 participant produced two drawings, *individual identity* was added as a random factor.  
460 Residual normality was graphically verified. The normality of the residuals of the random  
461 effect was graphically validated for each group. Since heteroscedasticity was detected across

462 groups in the original model, we added a covariance structure (*VarIdent*, adapted to the  
463 categorical variables) to allow the variance of the residuals to change according to group. The  
464 full model included all possible variables and first-order interactions between *group*, *gender*,  
465 and *condition*. We proceeded to model selection using a dredge function based on the lowest  
466 Aikake's Information Criterion (package *MuMIn*;  $\Delta\text{AIC} > 2$  (Barton, 2009)). Paired  
467 comparisons were made using the *lsmeans* package to compare different age groups in pairs.

468 Concerning the two additional metrics, the proportion of drawing in the sequence and  
469 the rate of state changes, measures have been done on the binary sequences. For the number  
470 of states changes, we normalized the data using a Box-Cox transformation and ran a Linear  
471 Mixed Model (package *nlme*) containing the variables *group*, *gender* and *condition* with  
472 *individual identity* added as a random factor. Again, model selection was carried out using the  
473 dredge function (package *MuMIn*) and we chose the model with the lowest AIC. Residual  
474 normality was graphically verified, but since heteroscedasticity was detected, we added a  
475 covariance structure to allow for a difference in the residuals variance between groups  
476 (*VarIdent*). For the proportion of drawing, we used a Linear Mixed Model (package *nlme*)  
477 too. The conditions of application (residual normality and homogeneity of variance) were  
478 graphically verified. The alpha level for all statistical analyses was set at 0.05.

479

480

### 481 **3. Results**

#### 482 3.1 Type of signal

483 Examination of  $\alpha$  through DFA (mean  $\pm$  sd =  $1.419 \pm 0.0490$ ) shows that the original  
484 binary sequences were characteristic of fBm. This result was confirmed by the <sup>low</sup>PSD method  
485 which estimates of  $\beta$  were greater than 1 (mean  $\pm$  sd =  $1.927 \pm 0.0472$ ).

486

## 487 3.2 Estimates of H

488 The Hurst exponent was estimated with the four methods (Supplementary Materials  
489 Figure 5). The binary time series studied being all fBm, we considered series resulting from  
490 the increments of these fBm. Each of the methods is positively correlated to the others, an  
491 expected result since they estimate the same coefficient (Figure 5).

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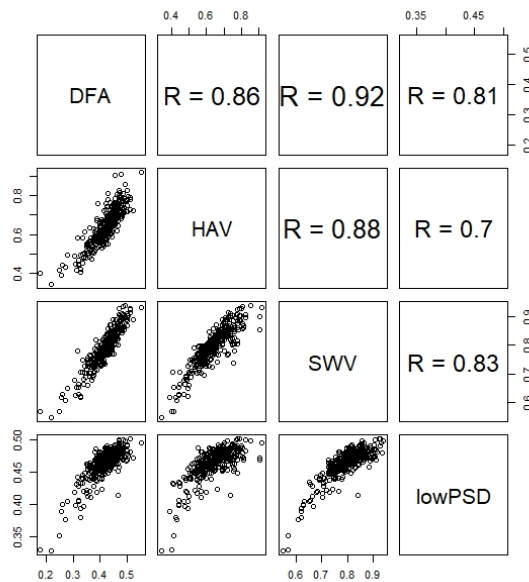
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502 **Figure 5.** Pearson correlation matrix indicated the correlation values between the four methods  
503 used to estimate the Hurst exponent H.

504

## 505 3.3 Combination of the estimators through a Principal Component Analysis (PCA)

506 Since the PCA was standardized, only the axes whose inertia was strictly greater than  
507 1 were kept, which was equivalent to keeping only axis 1 in our data set, explaining 87.68% of  
508 the variance (Correlation circle available in Supplementary Materials Figure 6). All  $H$   
509 estimators loaded positively into the first principal component, i.e. the Hurst axis (the  
510 loadings for DFA, HAV, SWV, and  $lowPSD$  were 0.513, 0.491, 0.518, and 0.475,  
511 respectively).

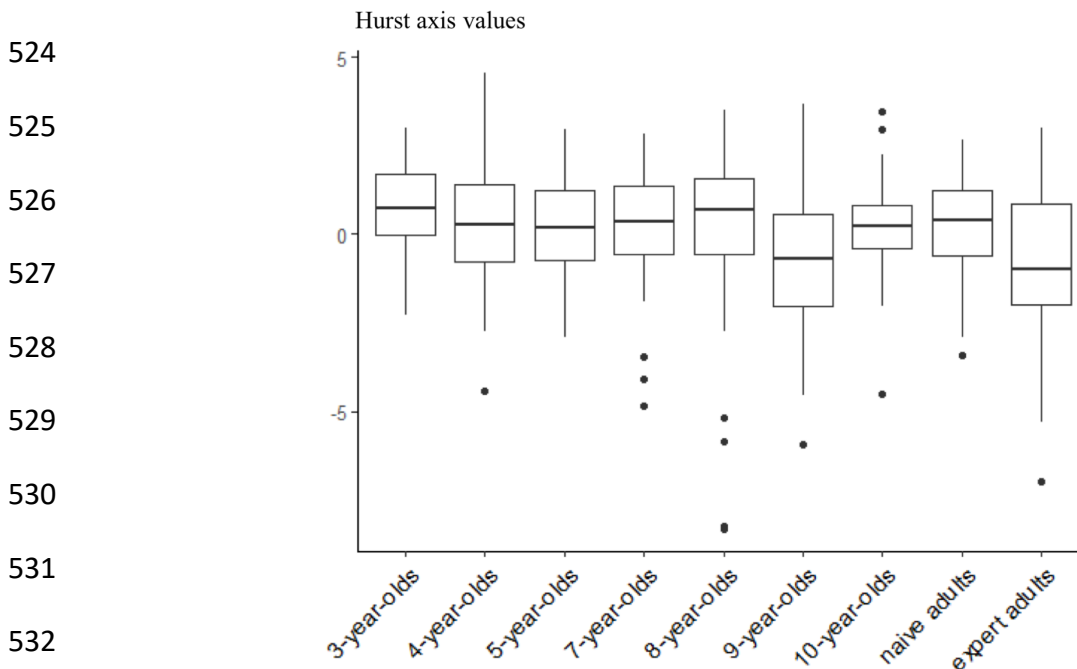
512

### 513 3.4 Variation in the Hurst axis according to the group

514 The selected model was the one that contained only the variable *group* ( $df = 8$ ,  $\chi^2 =$   
515 21.434,  $p = 0.006$ ; Figure 6). Paired comparisons indicated that two significant differences  
516 emerged: 3-year-olds had a higher value along the Hurst axis than novice ( $p = 0.0085$ ,  $t =$   
517 3.706) and expert ( $p = 0.0148$ ,  $t = 3.540$ ) adults. Neither gender nor condition was associated  
518 with variation in the Hurst axis.

519 Furthermore, values of the Hurst axis were highly correlated with the average value  
520 across our 4 estimators ( $r = 0.993$ ), and the same statistical model, containing only group as  
521 an independent variable, best explained variation in this averaged metric (Supplementary  
522 Materials Table 1).

523



533 **Figure 6.** Boxplots of the Hurst axis values for each group. Each boxplot depicts the median  
534 (bold bar), 25-75% quartiles (box) and outliers (points).

535

### 536 3.5 Additional temporal indices



537 *3.5.1 Proportion of drawing in the sequence*

538 The selection of models led us to choose the model containing the variables *group* ( $df$   
539 = 8,  $\chi^2 = 65.559$ ,  $p < 0.0001$ ) and *condition* ( $df = 1$ ,  $\chi^2 = 13.042$ ,  $p = 0.0003$ ). Naive adults  
540 showed a proportion of drawing significantly lower than that of all other participants ( $p <$   
541  $0.005$ ,  $t < -3.845$ ; Figure 7). In addition, the proportion of time spent drawing as higher in the  
542 *free* condition compared to the *self-portrait* condition ( $p = 0.0004$ ,  $t = 3.611$ ; Figure 7).

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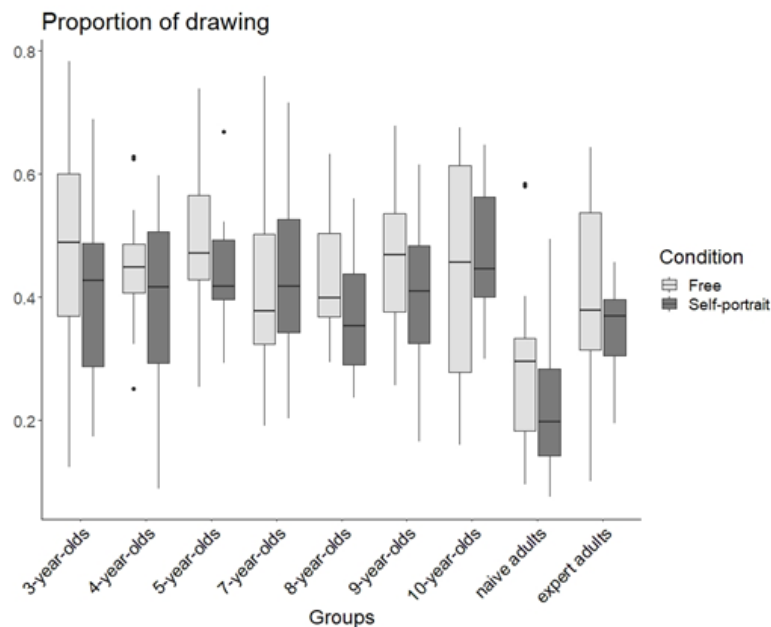
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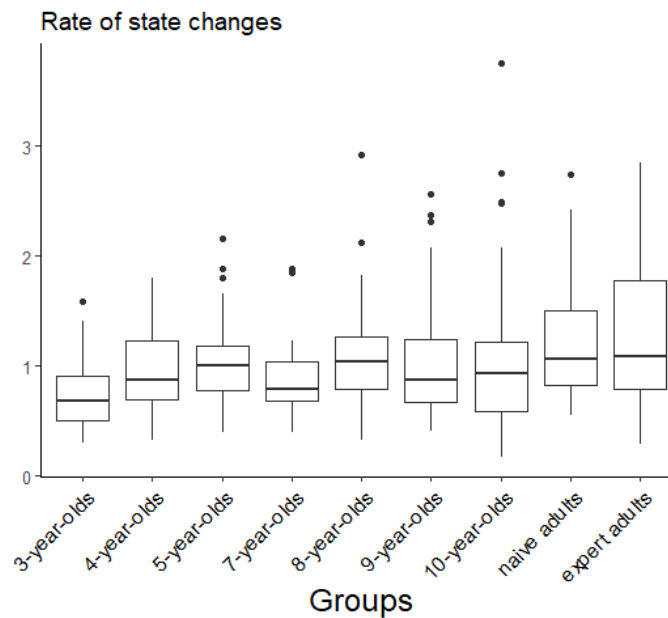
552 **Figure 7.** Boxplot of the proportion of drawing for each group and for both conditions. Each  
553 boxplot depicts the median (bold bar), 25-75% quartiles (box) and outliers (points).

554

555 *3.5.2 Rate of state changes*

556 The selected model was the one containing only the variable *group* ( $df = 8$ ,  $\chi^2 =$   
557  $32.607$ ,  $p < 0.0001$ ). The 3-years-old children alternate significantly less between drawing and  
558 interrupting behaviours than 5-year-olds ( $p = 0.0310$ ,  $t = -3.303$ ), 8-year-olds ( $p = 0.0262$ ,  $t =$   
559  $-3.359$ ) and adults, both naive ( $p = 0.0011$ ,  $t = -4.261$ ) and expert ( $p = 0.0009$ ,  $t = -4.303$ )  
560 (Figure 8). No other significant effects, gender or condition, were found.

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570 **Figure 8.** Boxplot of the rate of state changes (number of state changes per second) for each  
571 group. Each boxplot depicts the median (bold bar), 25-75% quartiles (box) and outliers  
572 (points).

573  
574

#### 575 4. Discussion

576 With this study, we wanted to know whether temporal fractal analysis could provide  
577 insight into the study of drawing behaviour, as has been done in other fields (MacIntosh,  
578 2014) but not yet – to our knowledge – to understand intermittence in drawing. Specifically,  
579 we tested whether the temporal dynamics of drawing varies according to the age, gender or  
580 instruction under which the drawing was carried out. In a previous study applying spatial  
581 fractal analyses in the field of drawing behaviour, we found that the efficiency of the drawing  
582 trajectory, defined as the correct reading of the drawing with minimal detail, increased during  
583 childhood and reached its maximum in children between 5 and 10 years of age, before  
584 decreasing in adults due to the addition of greater detail (Martinet et al., 2021). Studying  
585 temporal aspects should allow us to further understand the ontogeny of drawing behaviour.

586 We found a difference between the youngest (3-year-old children) and oldest (adults)  
587 participants, meaning that these two groups do not draw with the same patterns of alternation  
588 between drawing and non-drawing states. In other words, the process of drawing shows  
589 different degrees of temporal complexity. Young children showed the highest values of the  
590 Hurst axis, suggesting that they exhibit more stereotypical and therefore less complex  
591 temporal patterns in their drawing behaviour. On the contrary, temporal sequences of  
592 drawings were found to be more complex, meaning less predictable, in both naive and expert  
593 adults. In relation to this, the rates of state change we observed demonstrate that 3-year-olds  
594 performed significantly fewer alternations between drawing and drawing interruptions than all  
595 adults, 8-year-olds and 5-year-olds. Said differently, the drawings of the youngest children are  
596 composed of fewer strokes per unit of time spent on the activity.

597 In general, previous work has shown that 3-year-old children draw for shorter periods  
598 than older participants, get bored faster and may be more motivated by the simple motor  
599 pleasure of using the tablet rather than recognizing it as a real drawing support tool (Martinet  
600 et al., 2021). Many young children first tried each available colour, one by one, which might  
601 have induced a certain stereotypy in alternations between drawing and interruption, leading to  
602 high Hurst axis values. Their drawings were comprised of what could be called scribbles, as  
603 they were not figurative, not representative, at least to the eye of an external observer  
604 (Martinet et al., 2021).

605 However, 3-year-old children did not stand out in terms of the proportion of time spent  
606 drawing during a session. Indeed, all participants spent a greater proportion of their time  
607 drawing in the *free* condition than in the *self-portrait* condition, and we know from a previous  
608 study that the durations of the entire drawing sessions were also longer in the *free* condition  
609 compared to the *self-portrait* condition (Martinet et al., 2021). The present study confirms that

610 the addition of instructions limits the proportion of actual drawing time during a session by  
611 requiring more reflection time.

612         Regardless of the condition, the proportion of time spent drawing during a session was  
613 significantly lower in naive adults. Naive adults, more than any other group, expressed  
614 feelings of being judged and apprehension toward doing wrong, and expressed explicitly that  
615 they did not know how to draw. Despite these apprehensions and their alleged impacts on  
616 performance, the  $H$  estimates characterizing the drawing behaviour of naive adults was not  
617 different from those of experts. Whether this suggests that different mechanisms can lead to  
618 similar fractal patterns in drawing, or that such patterns are not sensitive to subjective  
619 experiences during drawing, cannot be determined at this time. However, this does highlight  
620 that the differences between young children and adults may not depend strongly on  
621 experience or skill but may instead reflect more fundamental ontogenetic processes.

622         Given that the majority of drawings made by 3-year-olds did not exhibit external  
623 representativeness, one possible explanation for this difference of complexity with age could  
624 be a desire for figuration. Indeed, in adults the process of drawing is intentional and may lead  
625 to greater stochasticity in the intermittences between drawing and non-drawing states, due to  
626 thought processes and/or tendencies toward representativeness. When an individual produces  
627 a figurative drawing, recognizable by an observer, the intentionality of his acts is obvious.  
628 Concerning abstract drawings, non-figuration does not necessarily mean absence of intention.  
629 The probable role of drawing instructions can then be evoked. This last consideration leads us  
630 to go further in future drawing analyses, asking adults to draw abstract or figurative drawings  
631 for comparison with children's' scribbles. As the temporal fractal index is a measure of the  
632 temporal complexity of the drawing behavioural sequence, if the two measures of  $H$  are  
633 different between the abstract drawings made by young children and those made by adults,  
634 this would mean that the complexity assessed by the  $H$  index could be interpreted as a

635 measure of intentionality more than just figuration. Additional studies would be needed to  
636 confirm this.

637         In the present study, drawing instructions (*free* and *self-portrait*) had no effect on  
638 drawing intermittence. Extrapolating from the previous discussion, inviting participants to  
639 produce archetypes, more stereotyped drawings of common objects such as a house or a  
640 flower, might produce a gradient of temporal patterns depending on the complexity of the  
641 task. Perhaps asking subjects to draw a specific object would lead to homogenization of  
642 temporal patterns across participants. Asking participants to reproduce a photograph – which  
643 would reduce the role of creativity and therefore minimize reflection time but not necessarily  
644 simplify the drawing task – may lead to further variation, and potentially reduced variability  
645 between subjects. The latter would allow measuring the variation in drawing complexity  
646 while removing cultural and normative aspects. In this way, it would be possible to reach  
647 stronger conclusions about the influence of a directive on drawing behaviour.

648         Concerning differences in drawing behaviour between individuals, gender can be an  
649 influential factor. Previous results have shown such differences in the fields of drawing and  
650 writing, particularly with regards to colour utilization, where girls show a more extensive use  
651 of colour than boys (Martinet et al., 2021; Turgeon, 2008; Wright and Black, 2013). However,  
652 we found no evidence to suggest that drawing intermittence differs between girls/women and  
653 boys/men.

654         Though we observed clear differences in fractal patterns of drawing intermittence  
655 between age groups, there remain limitations to the study. For example, difficulty arises from  
656 the fact that multiple methods exist to estimate the Hurst exponent, which often leads to  
657 conflicting results (Karagiannis et al., 2006). It remains challenging to determine which  
658 estimator best suits the type of data being analysed, and this is exacerbated by the fact that  
659 estimations themselves vary according to the method used even in simulated time-series with

660 *a priori* seeded Hurst values (Karagiannis et al., 2006). In our study, individuals with high (or  
661 low) H according to one method generally exhibited similarly high or low H with other  
662 methods, but the variations between groups differed from method to method. Indeed, different  
663 methods sometimes produced large differences in H for the same individual ( $\pm 0.3$ ). Such  
664 large differences interfered with conclusions about whether a drawing sequence was  
665 persistent or anti-persistent because in some cases H could be both above and below 0.5,  
666 depending on the method.

667 By applying new methods of analysis, it will be possible to progressively grasp the  
668 ontogeny of drawing behaviour. The results of a single study are not sufficient to identify the  
669 development of a behaviour as complex as drawing. Only a grouping of clues, each one  
670 characterizing one aspect of the behaviour, could make it possible to comprehend the whole.  
671 This work on temporal fractal analysis provides one piece that was previously missing and  
672 completes our previous research on spatial fractal analysis of drawings. Such works seem  
673 promising to better understand the ontogeny of drawing behaviour and, by extending this type  
674 of analysis to other species, notably great apes, we could learn more about its evolutionary  
675 history.

676

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684

685 **Author contributions**

686 Conceptualization, B.B., L.M., C.S.; Methodology, B.B. and L.M.; Investigation,  
687 B.B., L.M. and C.S.; Writing – Original Draft, B.B. and L.M.; Writing – Review & Editing,  
688 C.S., A.M, X.M. and M.P.; Funding Acquisition, C.S. and M.P.; Resources, J.H.; Data  
689 Curation, B.B. and L.M., Supervision, C.S. and M.P.

690

691 **Resource availability**

692 **Lead contact**

693 Further information and requests for resources and reagents should be directed to and will be  
694 fulfilled by the Lead Contact, Lison Martinet ([lison.martinet@iphc.cnrs.fr](mailto:lison.martinet@iphc.cnrs.fr))

695 **Data and code availability**

696 The dataset generated during this study are available at Zenodo :

697 <https://zenodo.org/record/5293436#.YStFntMzaYV>

698

699 **Declaration of Interests**

700 The authors declare no competing interests.

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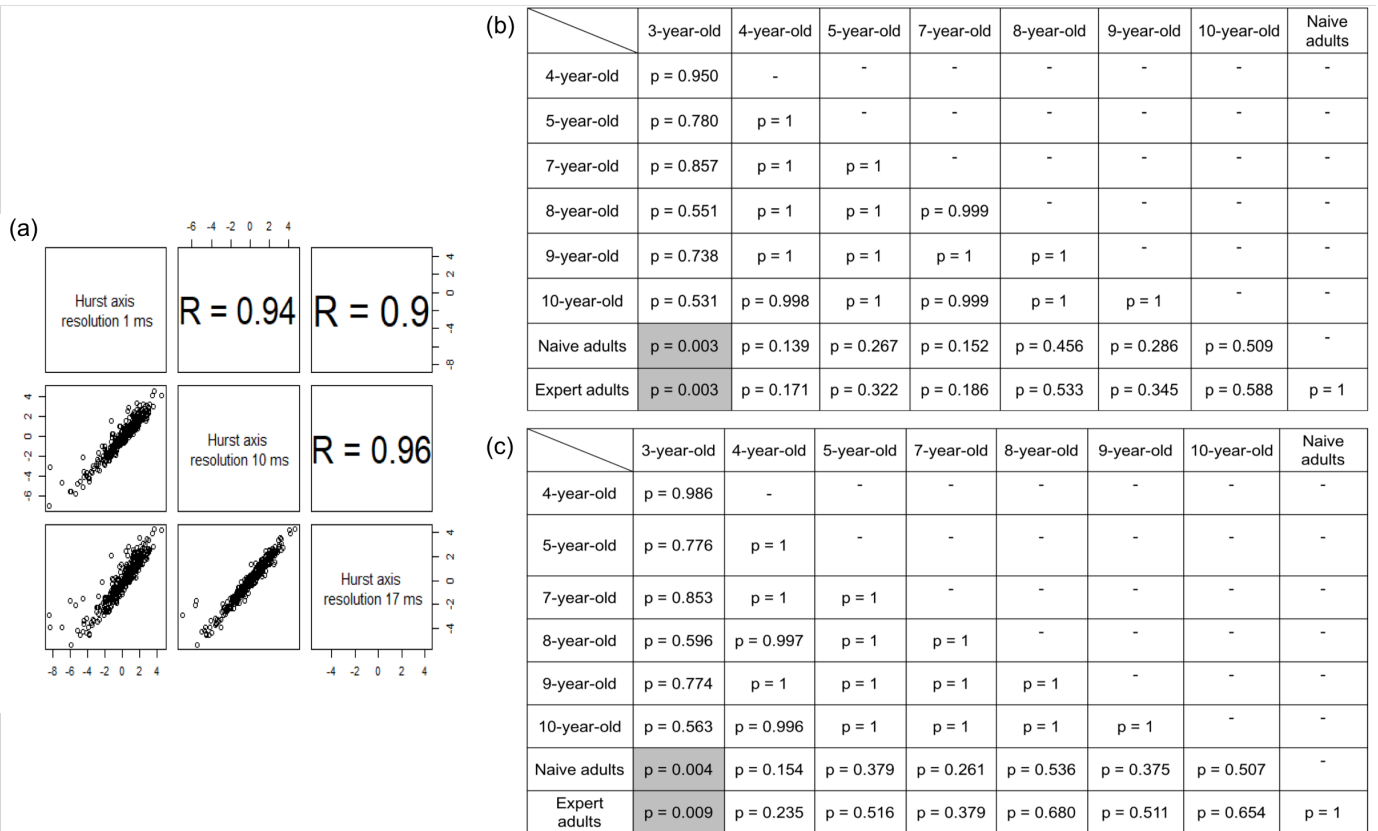
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822 **Supplementary Materials**



823 **Figure 1.** Analyses of different resolutions for the construction of the time series. (a) Pearson  
 824 correlation matrix indicated the correlation between the Hurst axis values obtained with 3  
 825 different resolution in the time series (1ms being the one used in the manuscript). (b) Pairwise  
 826 comparisons of groups obtained from the selected model (GLMM,  $df = 8$ ,  $\chi^2 = 25.811$ , =  
 827 0.001) with a time resolution of 10 milliseconds. (c) Pairwise comparisons of groups obtained  
 828 from the selected model (GLMM,  $df = 8$ ,  $\chi^2 = 23.23$ ,  $p = 0.003$ ) with a time resolution of 17  
 829 milliseconds. The different resolutions give the same results with the 3-year-olds showing a  
 830 higher value along the Hurst axis than adults, both, naïve and expert.

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832 To understand the impact of removing a period of time in the sequences, and to ensure this will  
 833 lead to consistent estimates, 50 drawings were randomly sampled. A chunk of 30 seconds was  
 834 then randomly removed from the whole temporal sequence for each drawing, and the remaining  
 835 parts were spliced. The 4 estimates were calculated on the first 50 seconds of the shortened

836 sequences of drawings. The correlation of these estimates and the corresponding estimates on  
837 the first 50 seconds of the non-modified sequences were calculated. The correlations were  
838 strong (DFA: 97%, SWV: 96%, HAV: 92%, lowPSD: 94%), showing the consistency of this  
839 methodology and its robustness to missing segments of data.

840 **Box 1.** Explanation of simulations showing the robustness of fractal estimates to random  
841 removals of segments within the sequence.

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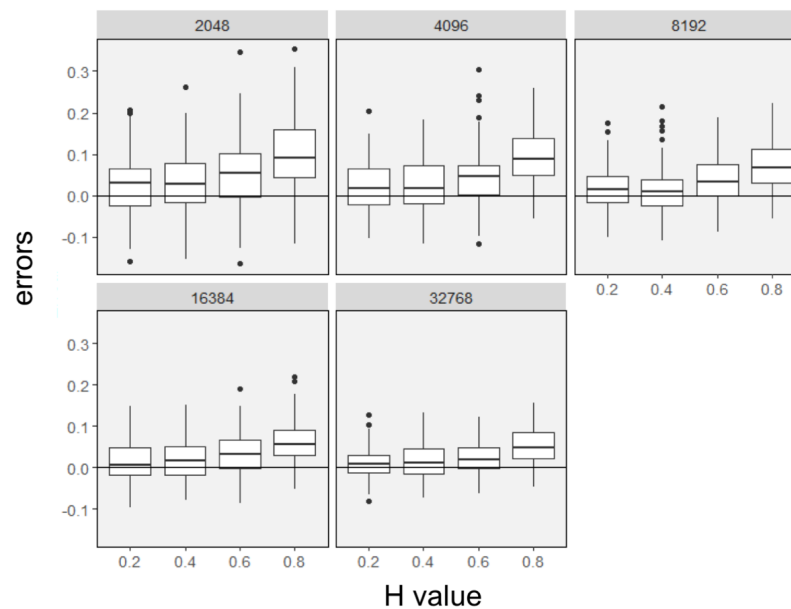
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851 **Figure 2.** Estimation errors of the estimates of Monte Carlo simulations with the HAV  
852 method by varying H and the length of the time series.

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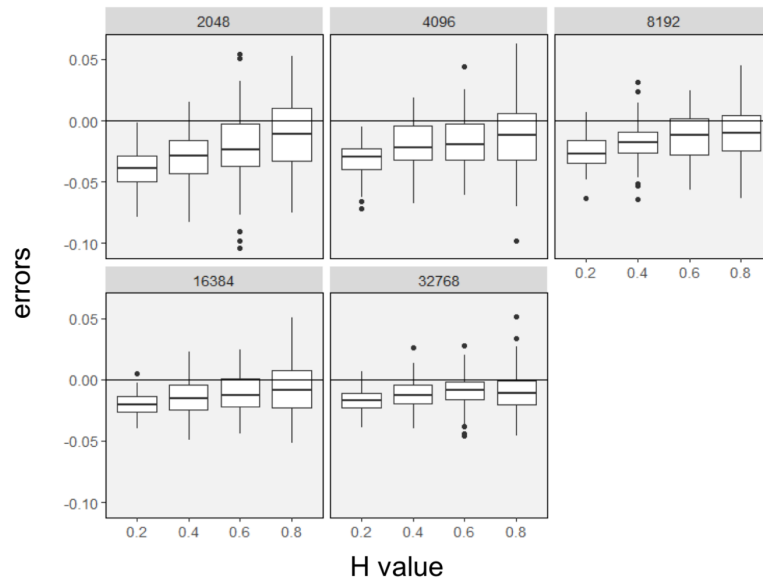
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869 **Figure 3.** Estimation errors of Monte Carlo simulations with the SWV method by varying H

870 and the length of the time series.

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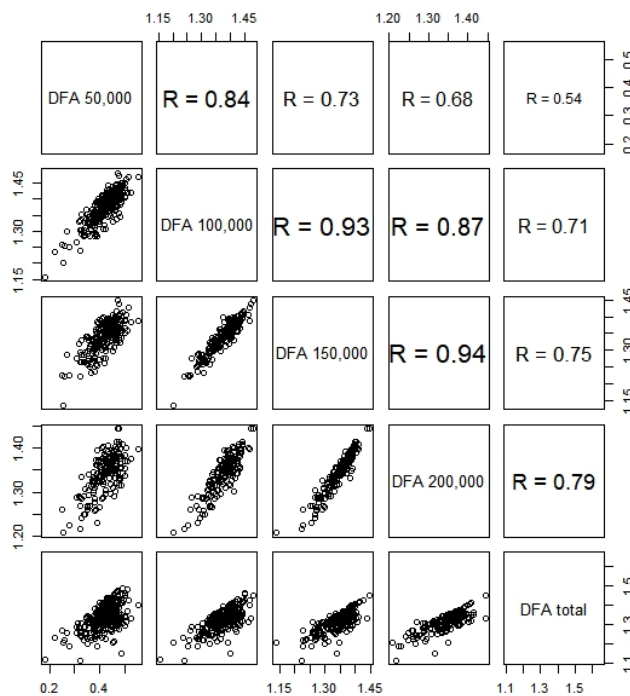
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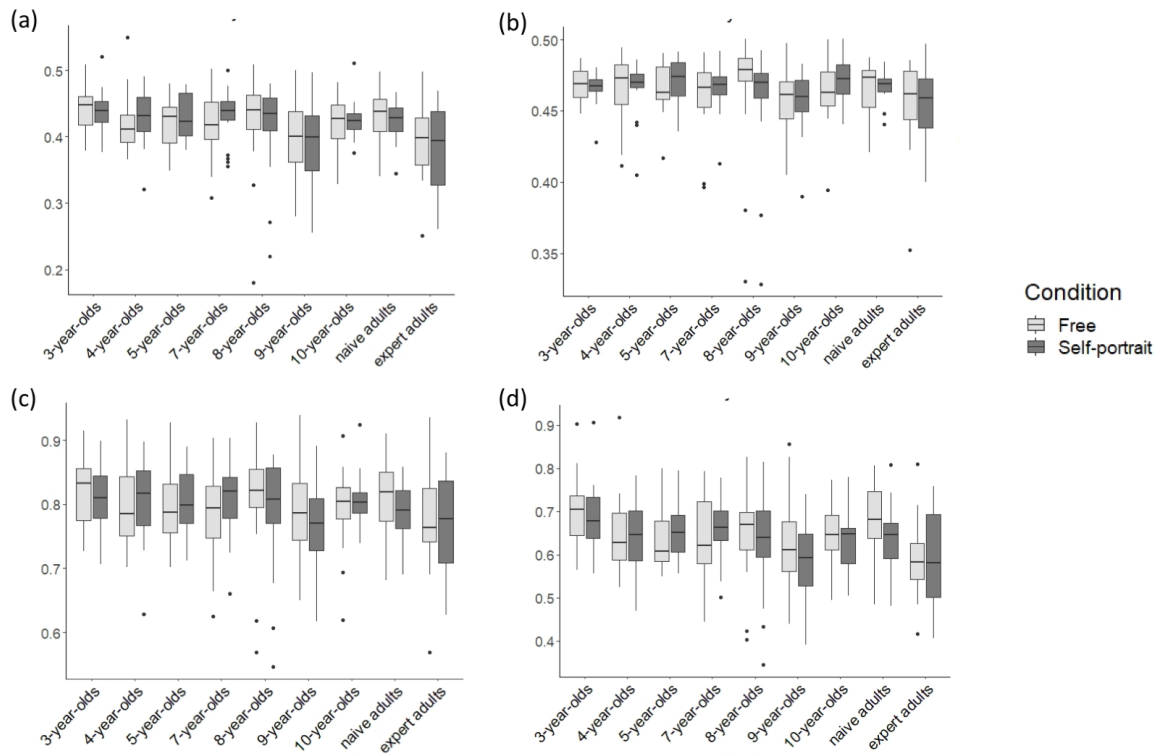
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881 **Figure 4.** Correlations between DFA coefficients based on the first 50,000 points, 100,000

882 points, 150,000 points and 200,000 points and the total length of the times series.

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884 **Figure 5.** Boxplots of the Hurst estimates calculated with four different methods. (a) Hurst  
885 exponent estimated with (a) the Detrended Fluctuation Analysis (DFA), (b) the Power  
886 Spectral Density analysis ( $^{low}PSD$ ), (c) the Scaled Windowed Variance (SWV) and (d) the  
887 Hurst Absolute Value method (HAV).



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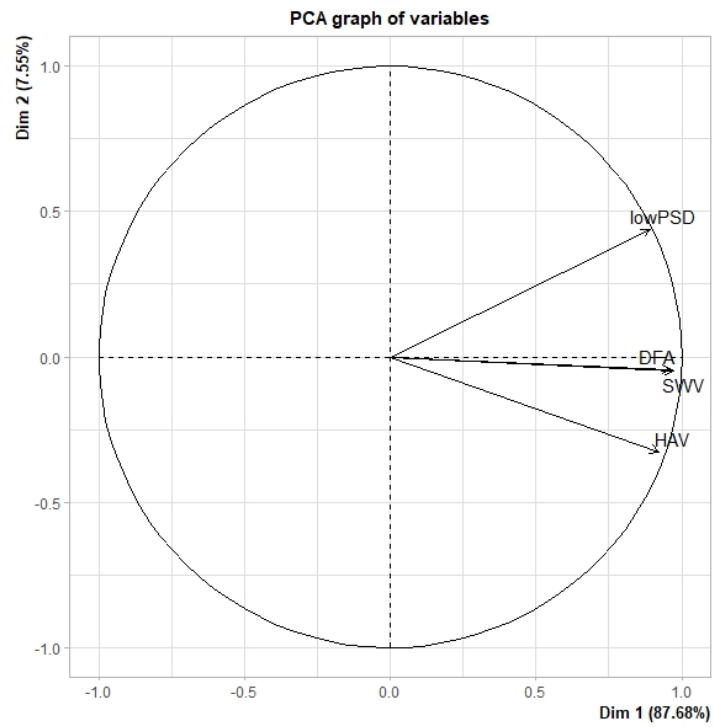
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899 **Figure 6.** Correlation graph of the variables.

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909 **Table 1.** Pairwise comparisons of groups obtained from the selected model (GLMM,  $df = 8$ ,  
 910  $\chi^2 = 22.842$ ,  $p = 0.003$ ) made by averaging the estimates of  $H$ .

|               | 3-year-old  | 4-year-old  | 5-year-old   | 7-year-old  | 8-year-old  | 9-year-old  | 10-year-old | Naive adults |
|---------------|-------------|-------------|--------------|-------------|-------------|-------------|-------------|--------------|
| 4-year-old    | $p = 0.950$ | -           | -            | -           | -           | -           | -           | -            |
| 5-year-old    | $p = 0.780$ | $p = 1$     | -            | -           | -           | -           | -           | -            |
| 7-year-old    | $p = 0.722$ | $p = 1$     | $p = 1$      | -           | -           | -           | -           | -            |
| 8-year-old    | $p = 0.832$ | $p = 1$     | $p = 1$      | $p = 0.1$   | -           | -           | -           | -            |
| 9-year-old    | $p = 0.701$ | $p = 1$     | $p = 1$      | $p = 1$     | $p = 1$     | -           | -           | -            |
| 10-year-old   | $p = 0.645$ | $p = 0.999$ | $p = 1$      | $p = 0.1$   | $p = 1$     | $p = 1$     | -           | -            |
| Naive adults  | $p = 0.004$ | $p = 0.139$ | $p = 0.319$  | $p = 0.273$ | $p = 0.271$ | $p = 0.332$ | $p = 0.621$ | -            |
| Expert adults | $p = 0.010$ | $p = 0.333$ | $p = 0.5682$ | $p = 0.186$ | $p = 0.502$ | $p = 0.587$ | $p = 0.849$ | $p = 1$      |