Making Drawings Speak Through Mathematical Metrics

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Abstract
Figurative drawing is a skill that takes time to learn, and it evolves during different childhood phases that begin with scribbling and end with representational drawing. Between these phases, it is difficult to assess when and how children demonstrate intentions and representativeness in their drawings. The marks produced are increasingly goal-oriented and efficient as the child’s skills progress from scribbles to figurative drawings. Pre-figurative activities provide an opportunity to focus on drawing processes. We applied fourteen metrics to two different datasets (N=65 and N=344) to better understand the intentional and representational processes behind drawing, and combined these metrics using principal component analysis (PCA) in different biologically significant dimensions. Three dimensions were identified: efficiency based on spatial metrics, diversity with color metrics, and temporal sequentiality. The metrics at play in each dimension are similar for both datasets, and PCA explains 77% of the variance in both datasets. Gender had no effect, but age influenced all three dimensions differently. These analyses for instance differentiate scribbles by children from those drawn by adults. The three dimensions highlighted by this study provide a better understanding of the emergence of intentions and representativeness in drawings. We discussed the perspectives of such findings in comparative psychology and evolutionary anthropology.

Keywords  Gestural drawings · Figurative and representational drawing · Evolutionary anthropology · Homo sapiens · Comparative psychology · Cognitive development
Drawing behavior takes time to develop; it proceeds over a series of childhood phases from scribbling in toddlers (Freeman, 1993; Kellogg, 1969) to representational drawing in older children. The act of drawing moves from purely motor pleasure without visual planning (Kellogg, 1969; Luquet, 1927; Golomb, 2003; Thomas & Silk, 1990) to more complex scribbling with aesthetic attentions (Golomb, 2003; Piaget & Inhelder, 2008; Willats, 2005) to full-blown representations. In terms of the development of early mark-making and pre-representational activities (Costall, 1995; Cox, 2005; Matthews, 1984; 1999), three steps have been identified: action representation, romancing, and guided elicitation (Adi-Japha et al., 1998; Matthews, 1984).

In humans, action representations, also called gestural drawings, appear both in spontaneous drawing and in response to the request to draw an object (e.g., an airplane). Children may accompany scribbling with verbalizations or sounds such as roaring, which indicates that both their motions and the marks emerging from their drawing instrument simulate the motion of an object. We can then speculate whether children are really scribbling or if they are simply demonstrating an active rather than a figurative mode of representation (Matthews, 1984). The personal actions of children are therefore not random but are intentional and combined with marks and sounds to represent the moving, roaring object (Cox, 2013; Gardner & Wolf, 1987; Wolf, 1988; Wolf & Perry, 1988). So the drawing has representativeness for the drawer (i.e., internal representativeness) even if this is not the case for an external observer (i.e., external representativeness (Martinet et al., 2021). Abstract art made by artists also has internal representativeness but sometimes not external because the art is not figurative. “Romancing” refers to instances in which children name a scribble with an object but an observer has difficulty finding a graphic resemblance between the scribble and the object the child claims to have drawn. Naming takes place either spontaneously or when elicited by an adult and can occur before or during the drawing, or after its completion. Action representations and romancing cannot be observed in children before they are two to three years old, or in children with certain psychopathologies such as autism (Charman & Baron-Cohen, 1993; Jolley et al., 2013). In these two situations, it is therefore difficult to establish if a drawing is goal-directed, having a meaning and an intentional representation. Evidence of intention is provided during the third step, called guided elicitation, when children show no representational intention in their free drawings but produce figurative drawings when assisted. However, even if it is not always easy to demonstrate intentional pre-representational activities, we can predict without difficulty that the marks produced are increasingly goal-oriented and efficient as the child progresses from scribbles to figurative drawings. Rather than studying the finished drawings, we should focus on the presence of pre-representative activities on drawing processes (Costall, 1995; Cox, 2005; Martinet & Pelé, 2021; Matthews, 1999). The aim of this paper is to demonstrate that mathematical metrics can give cues about intention and representativeness. Could these metrics enable us to measure the pre-representative activities that occur in the early stages of drawing?

Different methods have been used to answer this question of representativeness and goal directedness beyond drawing (Desmet et al., 2021; Urban, 2004). Published topics range from the kinematic aspects of scribbling to the precursors of graphic representation, including authors who compare curved lines in drawings to math-
ematical laws. Children tend to attribute representational meanings (e.g., an airplane) to angular curves and nonrepresentational meanings (e.g., a line) to smooth curves that they had just drawn (Kellogg, 1969). However, these studies are not objective given that the authors asked the children what their drawings represented a posteriori. Moreover, this methodology cannot be applied to nonverbal subjects (whether human or nonhuman primates) who are unable to explain their drawings. Thus, only one study to date has used methodology permitting the comparison of drawing abilities in humans and nonhuman primates or made it possible to understand the evolution of drawing in children and in other primates (Martinet et al., 2021).

This paper describes the use of different mathematical metrics with the aim of objectively and quantitatively measuring intention and representativeness in drawing. Just because the observer cannot identify an object or an intention in the drawing, since it is made by a toddler or it is abstract art, does not mean that intention and representativeness are absent. Is there a mathematical way to identify these concepts? Recently developed techniques make it possible to consider ethology as a physical science and apply quantitative measures in this discipline (Brown and De Bivort, 2018). Although simple drawing measures such as the number of colors can be used (Zeller, 2007), they provide few cues about the intention behind the drawing. We aim to go further by using mathematical measures to fulfil this goal. Metrics are already used to understand whether movements are optimal or evaluate the extent to which behavioral sequences are complex and predictable in animals, including humans. For instance, Martinet et al. (2021) and Beltzung et al. (2022) used spatial and temporal fractal analyses, which had previously been applied to understand optimal movements and optimal behavioral sequences of animals searching for food (Bartumeus et al., 2002; Meyer et al., 2017; 2020; Reynolds, 2008), and found an increase in complexity and efficiency in humans compared with chimpanzees, but also an increase with age in humans. Other metrics such as entropy (Ebeling et al., 2002; Kershenbaum, 2014) or the Gini index (Debache et al., 2019; Planckaert et al., 2019) were also used to understand the distribution or complexity of different behaviors (e.g., activity, food exchange, vocalization) from ants to humans. We used a total of fourteen metrics to enrich our understanding of the intentional and representational processes behind drawing. These metrics are detailed in Table 1 along with definitions and predictions.

This paper seeks to combine all of these metrics in different dimensions using principal component analysis. PCA is used to extract and visualize important information contained in a multivariate data table by combining metrics to form a biologically or psychologically significant dimension, as has already been shown for personality (Bousquet et al., 2015; Wolf and Weissing, 2012) or sociality (Viblanc et al., 2016). Here, we expect metrics to be combined and form dimensions that correspond to representativeness (at least internal, meaning from the point of view of the drawer, but not for the observer) and show evidence of anticipation (predictiveness of the sequence of behaviors), performance, or aestheticism in the drawing (Dis-sanayake, 2001; Matthews, 2003; Watanabe, 2012; Wolf and Perry, 1988). Temporal metrics and some spatial metrics based on fractal theory could indicate representativeness and anticipation while the use of colors and space could indicate a sense of aestheticism.
| Type             | Metric  | Definition                                                                                           | Meaning ("it measures") or expectation ("we expect")                                                                 | References                                      |
|------------------|---------|------------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------|
| Spatial metrics  | µMLE    | Spatial fractal metric, maximum estimate power coefficient of the drawing length distribution          | It measures drawing efficiency, from random trajectories to optimal trajectories indicating a representativeness          | Edwards et al., 2007; Sueur, 2011; Sueur et al., 2011; Viswanathan et al., 2008 |
|                  |         |                                                                                                      |                                                                                                                        | Janmaat et al., 2021; Mitani and Nishida, 1993; Papi et al., 1995                                                   |
|                  | Drawing distance | Total distance of drawing, from the first point to the last, in pixels                              | We expect long distance drawings to be more representative or contain more details than short distance drawings. However, it can also mean deterministic drawing, (i.e. no intention to represent anything). | Janmaat et al., 2021; Mitani and Nishida, 1993; Papi et al., 1995                                                   |
| Angle distribution metric | PCA dimension based on the coefficients of the cubic survival function of angle distribution (from 0° to 180°). Close to the Gini index in its calculation. | We expect homogeneous distributions of angles (low values of this metric) to indicate randomness (scribbles) whilst heterogeneous distributions should be linked to goal directedness (i.e., representativeness) | Bartumeus et al., 2008; Benhamou, 2004; Gurarie et al., 2016; Potts et al., 2018 |
|                  | Minimum convex polygon | Minimum polygon covering all drawing points and giving the percentage of drawing cover on the screen | We expect high covering to inform about representativeness but also the play/emotional interest in drawing              | Gaston and Fuller, 2009; Nilsen et al., 2008                                                               |
| Type               | Metric                      | Definition                                                                 | Meaning (“it measures”) or expectation (“we expect”)                                                                 | References                        |
|-------------------|-----------------------------|----------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------|-----------------------------------|
| Temporal          | Hurst index                 | Temporal fractal metric, measure of the long-term process in temporal sequence | It measures the temporal complexity of drawings sequences, from deterministic to complex, including both sequences of drawing and of non-drawing. | MacIntosh, 2014; MacIntosh et al., 2011 |
|                   | Gini index                  | Measure of the inequality among values of temporal drawing sequences distributions | We expect high Gini index, meaning unequal distribution of sequences to give an idea about intention and anticipation in drawing | Debache et al., 2019; Planckaert et al., 2019 |
|                   | Entropy index               | Measure of the temporal uncertainty of drawing                              | We expect a high entropy index to be linked to more representative drawing, including anticipation                  | Ebeling et al., 2002; Kershenbaum 2014; Leff, 2007 |
| Drawing test time | Total drawing time (including drawing time and non-drawing time) | We expect a long duration to inform about thinking about drawing, i.e., intention and representativeness                   |                                                                                                                     | Byrne et al., 2009; Noser and Byrne, 2014; Sueur, 2011 |
| Number of         | Number of drawing and non-drawing sequences during the test | We expect a high number of sequences to give an idea about goal-oriented behaviors, meaning intention and representativeness |                                                                                                                     |                                                                                 |
|                   | Drawing speed               | Speed of drawing, which is the drawing distance in pixels divided by the time of drawing | Speed is used as a measure of goal directedness or knowledge (i.e., in this context, mastering)                  |                                                                                 |
|                   | Drawing time proportion     | Drawing time divided by test time                                            | We expect a high drawing time proportion to inform on thinking about drawing, i.e., intention and representativeness |                                                                                 |
| Color             | Mean colorimetric profile   | Mean distribution of intensity levels for the Red, Green, or Blue colors, respectively, and after removing the white (screen) color on the parts covered by drawing | It measures the mean spectrum of colors used, from dark to light.                                                      | Martinet et al., 2021            |
|                   | Standard deviation of the colorimetric profile | Standard deviation of the distribution of intensity levels for the Red, Green, or Blue colors, respectively, on the parts covered by drawing | It measures the diversity of the spectrum of colors used. It is different from the number of colors as it takes also how much these colors are different. |                                                                                 |
The two objectives of this paper are to assess (1) whether mathematical measures can reveal patterns in drawing suggesting intention of representativeness and (2) whether these patterns and measures are linked to the age of the participants. More specifically, we hypothesize that objective and quantitative patterns in drawings will provide cues about the intentions and representativeness of the drawer, even if the observer fails to perceive an object or entity in the drawing. We used two datasets of drawings with different instructions in order to generalize results. We asked adults to make drawings of different patterns, including an abstract one. Then, we asked children and adults to draw with different instructions (e.g., self-portrait, free drawing, scribbling) in order to reveal these dimensions. We expect that drawings as scribbles would not exhibit similar dimensions if they are made by adults or toddlers, allowing us to attribute concepts behind each dimension. More precise predictions are given below for each metric. We expect children’s drawings to become more complex with age, being more efficient in terms of representativeness, including more color diversity and more sequences.

**Materials and Methods**

**Dataset**

All methods were performed in accordance with the relevant guidelines and regulations in France, checked and approved by the research ethics committee of Strasbourg University (Unistra/CER/2019-11). We used two datasets. The first is composed of drawing conditions expected to yield the greatest variation in drawings characteristics and then affecting the measures we used. The second is composed of drawing conditions used to test the effect of age and gender. The datasets are as follows:

1. We asked 13 adults (6 men, 7 women) from 21 to 29 years of age to make five drawings. These adults were considered “naive” insofar as they had never taken drawing lessons and did not draw as a hobby. These participants were students of the research institute where the authors worked. Each drawing corresponded to an instruction that was specifically designed to produce a range of drawings: (a) draw something with scribbles; (b) draw something with circles; (c) draw something with different angles; (d) draw something with a starry sky; and (e) draw something with fan patterns (fan patterns are defined as straight lines with sharp angles due to repetitive actions of hand, usually from right to left). The reasons for the choice of these five instructions are detailed with the list of metrics below. Examples for each instruction are given in Fig. 1. This dataset was collected in 2020 and is composed of 65 drawings.

2. The second dataset included both children and adults. A group of 144 children from three to ten years of age was split into 18–20 children per one-year age interval. Boys and girls were equally represented in these categories except in the youngest category, which was composed of 5 girls and 15 boys. In this study, the aim of including children was not to test for differences by age (that is the
next step) but to have a large panel of different drawings. The adult group was composed of 41 adults (21 men, 20 women) 21 to 60 years of age who were either naive or expert drawers. The latter were art school students and professional illustrators. Participation was voluntary for adults and subject to parental consent for children. None of the adults exhibited severe physical or cognitive traits that could impact drawing capacities. These two conditions were visually and verbally checked with participants. According to Martinet et al. (2021), all participants were asked to draw in two different conditions: free drawing (draw what you want: the experimenter told the subject that they could draw whatever they wanted, with no further instructions) and self-portrait conditions (draw yourself: the experimenter instructed the subject to draw themselves). The dataset was collected in 2018 and 2019. Further information about this dataset (i.e., methodology, examples of drawings, and video footage of hand movements) is given in Martinet et al. (2021). A total of 370 drawings was initially collected for this dataset; however, some data were lost during the recording processes. The final dataset therefore contains 344 drawings, but the distribution per age or sex categories was not affected. Three of the naive subjects are present in both datasets.

**Experimental Design**

The experimental design is similar to the one described in Martinet et al. (2021).

**Habituation Phase** Each participant was given a touchscreen tablet (iPad Pro, 13-inch, version 11.2.2, capacitive screen reacting to the conductive touch of human fingers) and was told to draw on it so they could be familiar with how it worked and how to change the color(s) they wanted to use. Drawing with fingers enabled very young children who had not yet mastered the use of a pencil to be included. A panel consisting of ten different colors was displayed at the bottom of the screen, and the participant could select a color by clicking on it. When they clicked on a different color in the panel, any subsequent drawing was produced in that color. Children

![Fig. 1 Examples of the five instructions we gave to participants for dataset 1: (1) Make a drawing with scribbles; (2) Make a drawing with circles; (3) Make a drawing with different angles; (4) Make a drawing with a starry sky; (5) Make a drawing with fan patterns](image)
were habituated to the touchscreens the day before the tests to avoid overstimulation. Adults were tested immediately after familiarizing themselves with the tablet.

Testing Phase Each child was individually tested during school hours at school, either in their classroom (for the 3-year-olds) or in the staff room (for the older children). The experimenter (LM or MP) stayed during the test but kept at a distance to avoid influencing the children. Adults were tested individually in a room at the research institute (for naive participants) or at the art school (for expert drawers). Adult participants were left alone in the room. A camera recorded the hand movements of all participants while drawing in case we needed to check for any problem during the session (interruption of the drawing, involuntary tracings, etc.). No time limit was applied.

Data Analysis

For each drawing, the spatial coordinates X and Y of every point of the lines drawn as well as their time coordinates [min; s; ms] and the color used were automatically scored on a datasheet (text file) by the iPad Pro. These data enable us to calculate spatial, temporal, and color metrics for each drawing (Table 1). Details of metrics, their calculation, and the range of values for each instruction for dataset 1 can be found in the ESM. The number of sequences is correlated to the number of lines in the drawing. We retain the number of sequences as data so the temporal sequences can be analyzed using the Hurst index and analyzed in parallel with the duration of each sequence.

For the first dataset, we expect different values based on the instructions provided to the participants:

1. Scribbles are usually more or less random patterns in toddlers, with no figurative intention but only locomotor pleasure. However, we expect adults to be less spontaneous in their scribbles. Scribbles should be done with few posing (non-drawing sequences) and drawing time should be short because there should be no figurative purpose or goal in this drawing condition in adults. For this reason, the scribbles are not expected to show sharp angles and straight lines, so we predict the observation of a small µMLE (Table 1) and a small angle distribution metric, but also a large minimum convex polygon. The drawing session duration and the number of sequences should be low but the drawing speed should be high. Finally, scribbles should have few colors.

2. We imagined drawing with circles would not result in sharp angles (but rather obtuse ones) nor straight lines, so we expect to obtain a small µMLE and a small angle distribution metric. We have no presupposition for the minimum convex polygon. Likewise, we cannot predict the drawing session duration or the number of sequences, whether in terms of speed or the number of colors used.

3. We imagined drawings with different angles to obtain large angle distributions as well as large distributions of line lengths, meaning an intermediate µMLE. We have no hypothesis for the minimum convex polygon. The number of sequences
should be high, corresponding to the different angles/lines, but we cannot predict the duration of the drawing session, the drawing speed, or the number of colors used.

4. Adults drawing a starry sky should draw randomly small stars on the paper sheet, separated by long distances. We therefore expect drawings of a starry sky to contain different angles, but mostly sharp ones depending on the stars’ shape. Long distances between stars but use of short lines to draw the stars should yield a high $\mu_{MLE}$. The minimum convex polygon, the number of sequences, and the drawing session duration should all be high since adults should draw the sky on the entire paper sheet. The number of colors should be low and the colors should be light unless the participants drew a dark sky.

5. Fan patterns are parallel broad zigzag strokes, meaning stereotyped or repeated sequences of straight and long lines separated by sharp angles (Pelé et al., 2021). We have no prediction for the minimum convex polygon. Speed should be high given the findings in previous studies on fan patterns (Kellogg, 1969; Zeller, 2007). The number of sequences should be high in relation to the different angles/lines. However, we have no prediction for the duration of the drawing session or for the number of colors used.

**Statistical Analysis**

As preliminary results, we analyzed whether and how each metric differs between drawings for each instruction. This was achieved using ANOVA, or a Kruskal-Wallis test when ANOVA conditions could not be met (i.e., non-Gaussian distribution). Pairwise comparisons were realized when ANOVA or Kruskal-Wallis tests were significant (the “TukeyHSD” function of the R base package and the “kruskalmc” function of the “pgirmess” package [Giraudoux et al., 2018], respectively). Only differences with $p<0.05$ were reported.

Analyses were carried out in three main steps using correlation analyses and principal component analyses: Analysis of the first dataset (as described below), analysis of the second dataset, following the same procedure as in step 1, and a final combined analysis of the datasets to generalize our results.

The first step, on dataset 1: a correlation analysis was carried out with the R package “PerformanceAnalytics” (Carl et al., 2010; Peterson et al., 2018) on all metrics to identify those that were highly correlated ($R>0.9$). Following this correlation analysis, we removed the drawing duration proportion metric, which was highly correlated to the Gini index. Most of the variables were also influenced by the drawing test duration metric. We therefore decided to correct all the variables by carrying out a linear regression, using each metric as a response variable and the drawing test time as a factor. We took the residuals from this linear regression, which corresponds to any variance of each point that was not explained by the drawing test duration. A principal component analysis (Budaev, 2010; Holland, 2008) with Varimax rotation was then carried out using the R package “Psych” (Revelle, 2011; Revelle & Revelle, 2015). Variables are automatically corrected to be comparable (mean and range). Three dimensions were set up. Varimax rotation is used to simplify the expression of a particular subspace in terms of just a few major items each. This means that the
Varimax rotation applies the variables to each dimension in turn in order to maximize the explained variance. We examined the loadings of each variable on each dimension. The loadings are interpreted as the coefficients of the linear combination of the initial variables from which the principal components are constructed. The loadings are equal to the coordinates of the variables divided by the square root of the eigenvalue associated with the component. We removed variables for which loadings are less than 0.4, which indicates a weak contribution to each dimension and to the total explained variance. After this removal, we renewed PCA with Varimax rotation and analyzed the results.

The second step, on dataset 2: We followed the procedure described for dataset 1.

The third step, on datasets 1 and 2: We compared the variables contributing to each of the three dimensions for the two datasets. We removed the variables that did not contribute to the same dimensions between dataset 1 and dataset 2 and performed a PCA with Varimax rotation on both datasets, checking that we obtained similar or better results and according to the parsimony rules (see Results). We did this as a way to compare all drawings using the same method and to generalize this analysis. These results were then compared to assess whether our procedure might be generalized to any dataset. PCA dimensions were compared via a Pearson correlation test. Finally, the same PCA procedure was used to combine both datasets and compare the scribbles made by adults following the instruction we gave (“draw something with scribbles”) and the “natural” scribbles of 3-year-old children. A Mann-Whitney test was performed to compare both categories in each dimension.

Finally, we tested the effect of age and gender in dataset 2. We ran generalized linear models (GLMs) with each dimension as the dependent variable and the gender of participants, age categories, and conditions (free drawing or self-portrait) as independent variables. We also added the interactions of gender–condition and group–condition as independent variables to the model. Normality and homoscedasticity of residuals were verified graphically. We then performed pairwise comparisons with Benjamini-Hochberg (Verhoeven et al., 2005) correction for significant independent variables. All analyses were performed in RStudio 1.4.1103 (Allaire, 2012; Racine, 2012). The significance threshold was set to \( \alpha=0.05 \).

**Results**

Preliminary results on dataset 1: the details of tests and pairwise comparisons between instructions (dataset 1) for each metric are available in the ESM. Three metrics showed similar values for the five instructions given to participants: angle distribution metrics, the mean colorimetric profile, and the standard deviation of the colorimetric profile. The minimum convex polygon was smaller in drawings composed of different angles than in fan pattern drawings. The number of colors was higher for the fan pattern instruction than in the different angles drawing. The scribble instruction results are different from all others in terms of drawing test time (i.e., lower), entropy (i.e., lower), number of sequences (i.e., lower), the Gini index (i.e., lower for all instructions except the starry sky), and the Hurst index (i.e., higher except in comparison with the fan pattern instruction). The starry sky instruction is linked to a
longer drawing distance than all other instructions except fan patterns, while the different angles instruction is linked to a shorter drawing distance. The different angles instruction has a lower drawing time proportion and a higher Gini index than all other instructions except “draw circles.”

First step on dataset 1: The results for the correlation analyses of metrics for the first dataset are shown in Fig. 2. Drawing duration proportion is highly correlated ($r = -1$) with the Gini index. We decided to remove drawing duration proportion as a variable. Moreover, as we could expect, 10 of the 13 variables are correlated with drawing session duration. The latter is the most correlated with other variables. We then corrected all remaining variables according to the drawing duration. The correlation chart describing these corrected metrics is shown in Figure S15. This step was followed by a PCA with Varimax rotation. The total explained variance is 55.7% (dimension 1 = 24.5%, dimension 2 = 17.2%, dimension 3 = 14%). Three variables
have a loading below 0.4 for all three dimensions (details in the ESM, Table S1), namely the angle distribution metric, the drawing session duration and the standard deviation of the colorimetric profile. We therefore removed these three variables from the dataset and carried out another Varimax rotation PCA. The total explained variance of this new PCA is 69.8% (dimension 1 = 31.9%, dimension 2 = 20.7%, dimension 3 = 17.2%). Each metric shows a higher loading value in one dimension, unlike the two others (Table 2). We can thus attribute each metric to one dimension as follows: dimension 1 (µMLE, drawing speed, Gini metric, entropy metric, drawing distance); dimension 2 (minimum convex polygon, mean colorimetric profile, number of colors); dimension 3 (Hurst index, number of sequences). Examples of dataset 1 drawings scaled to the three dimensions are given in Figure S16a–c.

Second step on dataset 2: We followed the same steps as those described for dataset 1. Results for the correlation analyses of metrics of the second dataset are shown in Figure S17. The results of dataset 2 are comparable to those of dataset 1: the drawing duration proportion was highly correlated to the Gini index (R = 1), and was therefore removed to correct other variables by the drawing duration. The correlation chart depicting these corrected metrics is shown in Figure S18. This step was followed by a Varimax rotation PCA. The total explained variance is 55.3% (dimension 1 = 18.7%, dimension 2 = 18.4%, dimension 3 = 18.2%). As in dataset 1, the angle distribution and the drawing session duration have a loading below 0.4 for each dimension. However, the standard deviation of the colorimetric profile has a loading equal to 0.87 for dimension 1. We removed this variable to ensure a fit with the results of dataset 1; this does not change the variance explained (64.6% with versus 64.7% without) or the contributions of other metrics to the different dimensions. We carried out another Varimax rotation PCA. The total explained variance of this new PCA is 64.7% (dimension 1 = 24.2%, dimension 2 = 23.5%, dimension 3 = 17.1%). Each metric shows a loading value higher in one dimension, unlike the two others (Table 2). We can thus attribute each metric to one dimension as follows: dimension 1 (µMLE, drawing speed, drawing distance, minimum convex polygon), dimension

Table 2 Loadings of the metrics (after loadings selection) on the three Varimax rotation PCA dimensions of the two datasets. Bold values indicate the dimension in which the metric is retained in each dataset. Shading indicates similar results for both datasets. Axes of Dimension 1 are inversed between the two datasets, but results and correlations are similar

| Metric                  | Dataset 1 | Dataset 2 |
|-------------------------|-----------|-----------|
|                         | Dim. 1    | Dim. 2    | Dim. 3    | Dim. 1    | Dim. 2    | Dim. 3    |
| µMLE                    | 0.608     | -0.389    | -0.303    | -0.781    | -0.276    |
| min. conv. pol          | -0.374    | 0.783     | 0.134     | 0.666     | 0.404     | -0.133    |
| Hurst index             | 0.214     | -0.881    | -0.138    | -0.911    |
| No. of sequences        | -0.131    | 0.79      |           | 0.775     |
| Drawing speed           | -0.914    | 0.104     | 0.867     | -0.111    | 0.245     |
| Gini index              | 0.784     | 0.19      | 0.211     | -0.14     | 0.42      | 0.685     |
| Entropy index           | 0.659     | 0.363     | 0.212     |           |           | 0.45      |
| Mean color. profile     | 0.437     | 0.711     | -0.191    | -0.168    | 0.857     |
| No. of colors           | 0.11      | 0.759     | -0.144    | 0.181     | 0.607     |
| Drawing distance        | -0.754    | 0.223     | 0.708     | -0.488    | -0.296    |

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Third step on datasets 1 and 2: Seven of the ten retained variables belong to the same dimension in the PCAs carried out for datasets 1 and 2 (Table 2), and have quite similar loadings. However, three variables (minimum convex polygon, entropy index and Gini index) are not found in the same dimensions in the two datasets. When these three variables were removed from the PCA, we obtained similar results with comparable loadings per metric (Table 3) and 77.5% of the variance was explained for dataset 1 (dimension 1 = 31.9%, dimension 2 = 23.2%, dimension 3 = 22.4%), whilst 77% of the variance was explained for dataset 2 (dimension 1 = 31%, dimension 2 = 26.1%, dimension 3 = 19.9%). Reducing the selection of variables from ten to seven does not substantially change the classification of drawings, as the values of the three PCA dimensions are highly correlated between the first and the third step in dataset 1 (RC1: $t = 18.942, df=63, p<0.0001, r=0.92$; RC2: $t=14.357, df=63, p<0.0001, r=0.87$; RC3: $t=-15.764, df=63, p<0.0001, r=0.89$). When we combined both datasets, we obtained similar results to those obtained in separate analyses of dataset 1 and dataset 2, with 77.5% of the variance explained (dimension 1 = 30.2%, dimension 2 = 25%, dimension 3 = 20.2%; Table 3). Examples of dataset 1 drawings scaled on the three dimensions are given in Fig. 3. Finally, we compared the three dimensions between scribbles of dataset 1 (made by adults) and scribbles of dataset 2 (made by 3-year-old children only, as scribbles become rare from the age of four onwards) in order to show that the PCA is able to show differences between drawings unable to see with our human eyes. Mann-Whitney tests showed that dimension 1 differs between datasets 1 and 2 ($w=29, p=0.0066$) whilst there is no significant difference between the two sets for dimension 2 ($w=107, p=0.122$) and dimension 3 ($w=105, p=0.152$) (Fig. 4). Moreover, Fig. 4 shows that data are more dispersed for the three dimensions in adults’ scribbles compared to children ones. Mann-Whitney test for each metrics in each dimension are detailed in the supplementary material (Table S2).

Effect of age and gender on dataset 2: With respect to the GLMs, the model selection of each dimension and the results for each variable are detailed in the ESM (Tables S3–S8). Interactions were only present in the models which best explained dimension 2 variance, but were not significant (conditions: gender, $p=0.139$). Gender did not influence any of the three dimensions ($p>0.097$). The drawing condition only influenced the dimension 2 ($p=0.016$), with higher values for the free drawing.
indicating a higher number and spectrum of colors were used. Age categories influenced all three of the dimensions (Fig. 5). Pairwise comparisons (Table S9) showed that dimension 1 values of 3-year-old children were lower than that of 5-, 7-, and 9-year-old children ($p<0.044$), as was the ones of expert adults ($p<0.03$). This means that we observed an increase and then a decrease with maximum efficiency around 9 years of age. Dimension 2 values (Table S10) were higher in 3-year-old children than in other categories ($p<0.03$), except that of 4-year-old children and novice adults. A higher dimension 2 was noted in 4-year-old children compared with that of 7-, 9-, and 10-year-old children and expert adults ($p<0.004$). A lower dimension 2 was
noted in 9-year-old children compared with that of 3-, 4-, 5-, and 8-year-old children and novice adults \( (p<0.03) \). Novice adults showed a higher dimension 2 than 9-year-old children and expert adults \( (p<0.03) \). There was a general decrease and then increase in the dimension 2 as young children, older children, and novice adults added more colors than middle-aged children and expert adults. Finally, dimension 3 values (Table S11) of novice adults were higher than that of all other age categories \( (p<0.004) \). Expert adults showed higher dimension 3 values compared with 3-, 4-, and 7-year-old children \( (p<0.038) \).
Discussion

We used several mathematical metrics to characterize drawings and assess whether they can give cues about representativeness and intention. Principal component analyses helped us to organize these metrics in three dimensions in a first dataset. The analyses on this first dataset were then confirmed with the analyses carried out on a second dataset, thus allowing us to generalize our method of characterizing drawings and the subsequent results. This study is an important step in the analysis of drawings as it is the first time that such a high number of mathematical indices are used to analyze the cognitive processes behind creativity. This discussion seeks to understand which process corresponds to each dimension provided by the PCA.

The choice of two datasets that each involves different drawing instructions proves to be the right protocol to obtain variations in each metric. The colors used to draw are influenced by the instructions we gave. The choice of these instructions was designed to produce a variety of shapes and lines influencing spatiotemporal metrics. However, variation in used colors is still high and two color metrics (i.e., number of colors and mean colorimetric profile) partly explains variance in different dimensions. Nevertheless, the standard deviation of the colorimetric profile does not provide any information about the drawing, as the choice of colors variable is more a question of personal preference than characteristic of any representative process. Similarly, and contrary to what we expected, the angle distribution metric does not differ between the instructions of dataset 1 and did not play any role in explaining variance in the PCAs of dataset 1 and dataset 2. This result might be due to the issuing of an unsuitable instruction, thus leading to false negatives. However, as we obtained similar results between dataset 1 and dataset 2, the explanation should be more in the drawing process itself where, whatever the objects, their representation produces similar angle distributions. The study of turning angles is often used when assessing the optimality of animal movements, but it is limited to differentiating random movements from goal-oriented and directed ones (Reynolds, 2008; Sueur, 2011; Sueur et al., 2011). The scale used to analyze angles in our study is possibly too limited to obtain significant results. After correcting all variables according to the drawing session duration, no difference is seen in the latter between instructions, nor did it play a role in explaining PCA variance in either of the datasets. This means that representativeness and aestheticism in drawing are not directly linked to drawing duration but more to all the other processes (e.g., the drawing traits length and the number of sequences depending on the number of objects) that influence the duration of drawing. In dataset 1, scribbles were the only instruction leading solely to nonrepresentative drawings, despite the fact that the definition of a scribble can be unclear. Other instructions mainly resulted in the drawing of objects or animals. It is difficult to assess whether it is the instruction itself or the process of drawing scribbles that leads to nonrepresentative drawings, but scribbles show the highest difference with other instructions for many metrics in dataset 1. Although it is possible to draw a figurative drawing using scribbles, no such cases were observed in our study. This is certainly because participants had toddler scribbles in mind when we gave the instruction. Observation of these differences shows that the process of drawing scribbles results in the rapid drawing of a small number of short sequences of relatively random lines.
Closer evaluation of the principal components analyses shows that some metrics obtained a high loading but were not found in the same dimensions in dataset 1 and dataset 2. This was the case for the minimum convex polygon, which does not show substantial differences between the instructions of dataset 1. We would expect the minimum convex polygon to be a proxy of representativeness or aestheticism by filling the screen, but toddlers are reported to fill the paper sheet when drawing (Kellogg, 1969; Matthews, 1984; Wolf, 1988). Indeed, the minimum convex polygon was also shown to be high with scribbles or other nonrepresentative drawings (see Fig. 3), which indicates that this metric cannot be used to understand the cognitive processes underlying drawing. The Gini and entropy indices, both measured on temporal sequences of drawing, also belong to different dimensions in datasets 1 and 2. The Gini index is a measure of the inequality of temporal drawing sequences whilst entropy is a measure of the temporal uncertainty of drawing. Both measures could be developed to other aspects of the drawing (for instance, spatial Gini index and angle Gini index), but we think that our measures already covered these aspects and that adding other measures could overlap with the existing ones. Indeed, the duration of drawing sequences is linked to the lengths of the drawing lines for each object in the drawing. This can be seen in the different correlation charts, where temporal metrics are correlated to spatial ones. Given this uncertainty in the explanation of the dimensions of datasets 1 and 2, we preferred to remove these two metrics. However, PCA results did not change after this removal and the explained variance was higher. The Gini and entropy indices are increasingly used in different studies, despite a continuing debate about their interpretability (Ben-Naim, 2012; Leff, 2007; Lerman and Yitzhaki, 1984). Future works are required to assess their potential role in the domain of drawing and other behaviors. Moreover, the Gini index is ineffective when calculated on binary sequences and does not provide any new information. Perhaps considering the cumulative sum of drawing and non-drawing could lead to meaningful results.

After the different steps of selection of variables, we reached similar results between datasets 1 and 2 and explained almost 80% of variance. This result is important because it means that whatever the dataset and the given instructions, our method could be applied to analyze drawings. However, this method is only valuable if the dimensions of the PCA have a biological or psychological aspect.

Dimension 1 is composed of the drawing speed, the drawing distance and the $\mu$MLE (see Table 1 for definitions). In movement ecology, the drawing speed is a proxy of goal directedness—in other words, the intention of an animal to go to a specific place that it knows (Byrne et al., 2009; King and Sueur, 2011; Noser and Byrne, 2014; Sueur, 2011). The higher the motivation to go to a place where resources can be found, the higher the speed. In our drawing context, speed can be a proxy of intentionality and of mastering, meaning that participants who are familiar with what they are drawing do it faster. We observed this tendency in dataset 2, where the mean drawing speed of experts was $0.73 \pm 0.37$ compared with $0.56 \pm 0.27$ for naive participants. However, drawing speed is also high for scribbling toddlers or for someone who wants to fill the screen (or paper sheet) with one color, and in both of these cases, drawing speed is linked to drawing distance. This is what we obtained in our results (Tables 2 and 3; Fig. 3) with many participants coloring the starry sky blue.
or black. This adds detail without providing a better representativeness of the drawing. On the other hand, \( \mu \text{MLE} \) is negatively correlated to drawing speed and drawing distance, and is used in ecology to evaluate the efficiency of animal trajectories. In an environment with different food resources, an animal can move randomly or go directly to the resources area. In this case, movements are efficient and optimal and \( \mu \text{MLE} \) is high. We qualified these movements as a Lévy flight (or walk) (Reynolds, 2008; Viswanathan et al., 1999). In our drawing study, a high \( \mu \text{MLE} \) indicates an efficient drawing, i.e., it is representative, intentional and with few details (see Fig. 3). It is easy to recognize what the drawer wanted to draw, but drawing distance is low and indicates few details. If we could link an ability to this dimension 1, it would be efficiency. In this way, we suggest the dimension 1 to be close to the concept of efficiency. Indeed, efficiency can be defined as an ability to avoid wasting materials, energy, efforts, money, time, etc. Efficiency is different from effectiveness, which is the capability of producing a desired result or the ability to produce desired output (Frøkjær et al., 2000; Marley, 2000). In our study, we suggest that effectiveness is representativeness, whilst efficiency is representativeness combined with few details (i.e., optimality). Efficiency might be illustrated in a sketch (Mihai & Hare, 2021; Xu et al., 2020) and by emoticons (Huang et al., 2008; Takahashi et al., 2017).

Importantly, the scribbles made by adults showed higher values of dimension 1 than scribbles by toddlers. This is particularly due to higher drawing speed in adults (Table S2). The number of sequences is also higher for adults’ scribbles, but the number of colors is lower. This may indicate that even if these drawings do not have an external representativeness, they may have an internal representativeness for adult participants. This also means that our analysis is able to show differences between drawings unable to see with our human eyes. Representative drawings do not mean figurative, in the way that an external eye sees something—objects or persons—drawn on the paper, but representative means that the drawer have something in mind to draw and this can be abstractive for instance.

The second PCA dimension is composed of the number of used colors and the mean colorimetric profile. Adding and diversifying colors facilitates the differentiation of objects in a drawing. When there are few details in a drawing, one color is enough to identity the object but when more details are present, the use of colors makes it easier to identify the different objects. This principle can be observed in Fig. 3a, for instance, with the drawings of the crab (one color) and the house (different colors to identify the flowers, the car, the butterfly, etc.). Colors facilitate the visual perception of objects and materials in our environment (Castelhano and Henderson, 2008; Witzel and Gegenfurtner, 2018). In our drawing datasets, this cognitive process is found to make drawings easier to interpret and increase their external representativeness. We suggest the dimension 2 to represent “diversity” of colors in terms of number and panel.

Finally, the third PCA dimension is composed of the Hurst index and the number of sequences, both of which are temporal metrics. The number of sequences is directly dependent on the number of lines drawn (whatever their length), i.e., the number of forms that are either objects or components of an object. The Hurst index is a proxy of the temporal complexity of a drawing. It indicates how far the timeline of a sequence can predict another sequence. For instance, two drawings can contain the
same number of sequences, but one will be considered as deterministic (small values of dimension 3, not complex, for analyses of dataset 1) if the duration of sequences is similar (because the drawn objects are all similar), whilst the other will be considered stochastic (high values of dimension 3) and more complex if the sequences cannot be predicted because they followed an unpredictable pattern (which is the intention when representing different objects). Such examples can be seen for instance in Fig. 3b and c (a drawing that resembles a rose window and the drawing with planets) for dataset 1. Here, higher values in dimension 3 seem to indicate higher anticipation and intention in drawing. We suggest dimension 3 to be close to the concept of sequentiality. When the complexity of the drawing increases to make something representative, the number of sequences and the stochasticity increase.

As expected, age influenced the three dimensions of drawing in dataset 2. The first dimension represents the µMLE spatial fractal index, drawing distance, and drawing speed. It provides an insight into the representativeness and intentionality behind a drawing, even an abstract one; as well as the details needed to make a drawing figurative, such as the drawing distance. As such, the relationship between age and dimension 1 is nonlinear and dimension 1 initially increases, then decreases with age. This trend has previously been found with the µMLE spatial fractal metric (Martinet et al., 2021) but the dimension 1 from the PCA in this study gives more discriminative results. The dimension 1 increases in young children can be easily explained by the progressive development of more controlled and goal-oriented lines which often underlie the production of figurative drawings. Conversely, 3-year-old children are more motivated by motor pleasure alone when producing scribbles (Kellogg, 1969); therefore, dimension 1 is lowest for this age category. Thereafter, dimension 1 increases in 7- to 8-year-old children and decreases in 10-year-old children and adults. At 7 and 8 years of age, children draw all the parts of the object they have in mind without abstraction or unnecessary details (Baldy, 2011; Kellogg, 1969). Their primary goal is to be understood (external representativeness) with no aesthetic goals, which ensures that their drawings are more efficient. Adults’ drawings appear more complex because of the compilation of numerous details. Furthermore, adult representations may be subject to other influences, such as social norms, which young children are not (Itskowitz et al., 1988); and our results in the two other dimensions confirm this. The dimension 2 represents the diversity and number of colors used. Young children are more motivated by the desire to play rather than drawing; thus, they try more colors and return the highest diversity values. Dimension 2 is also higher among novice adults due to their willingness to add more details. Children 7–9 years of age have the lowest diversity as their drawing efficiency is high. Dimension 3 represents the number of sequences and the temporal complexity of alternations; and it generally increased from the youngest children to the adults. Very young children draw with scribbles using few sequences, and are more deterministic than their older counterparts. Adults tend to add many details; as such, they present the highest number of sequences and alternations between drawing and interruption resulting in a higher complexity. Therefore, the higher the dimension 3 in adults results in a lower dimension 1. Furthermore, the study of drawing’s temporal components completes the spatial analysis and allows us to further understand the ontogenetic development of drawing behavior.
We also tested two other factors in dataset 2: the gender of the participants and the conditions of the drawing sessions (i.e., free drawing or self-portrait). Gender had no significant overall effects on the drawing dimensions, barring a minor influence on dimension 3. In a previous study, Martinet et al. (2021) found that gender had an effect on color use but not on the µMLE spatial fractal metric. Other studies have shown that girls use more colors than boys in their drawings (Milne and Greenway, 1999; Wright and Black, 2013), but this mainly depends on the age of the children (Turgeon, 2008) and the instructions that they receive. Our results indicate that a higher number and more diverse spectrum of colors were used in free drawing versus self-portrait conditions, which may mitigate the gender effect. The open nature of free productions increased the use of colors, whereas the limitations imposed by self-portrait conditions lead individuals to use fewer elements when composing their drawing. (Martinet et al., 2021) also found that all age groups spent more time drawing under the free condition than under the self-portrait condition. This is an important bias to consider when thinking about research protocols, as the instructions given to participants appear to constrain their drawing process and may influence the results.

Our study identifies three dimensions in drawing that we propose to represent the concepts of efficiency, diversity, and sequentiality. All three dimensions facilitate our understanding of drawing representativeness. This statement can be observed in Fig. 3, where we can easily determine the intentions of participants, even if the drawing is abstract (i.e., there are no identifiable objects). The combination of these three dimensions allows us to judge the representativeness of a drawing even if it does not seem to represent anything for the observer and that the drawing is not figurative. In this way, we mean that if a person makes a drawing with (1) high speed and long lines, (2) many colors, and (3) many sequences, the drawing will get a high score and should be categorized as highly representative, in the way that these conditions cannot be met without a deep and strong reflection of the drawer. One condition taken apart can be the sign of motor development or locomotor pleasure, but our combined results allow us to determine if a drawer has an intention behind nonfigurative and abstract drawing. The fact to ask participants in this study abstract and nonfigurative drawings and that their dimension values, contrary to children’s drawings, are closer to figurative drawings indicate the representativeness. The perspectives of this study are therefore noteworthy: we can use this method to evaluate the intentions behind a drawing that has no meaning for us, as adults with no psychopathologies. In this respect, we identify three perspectives: (1) We can study the ontogeny of drawing in children and identify with precision the premises of the different steps observed during the drawing learning process (action representation, romancing and guided elicitation). This part perspective is partly done in this study showing an effect on age on the three drawing dimensions but we need to go deeper in this ontogeny approach. (2) We can also extend the study to other species, particularly great apes, which are known to draw, and assess whether their drawing is motivated by internal representativeness (Martinet and Pelé, 2021). (3) Finally, the method can be extended to psychopathologies such as autism (Charman & Baron-Cohen, 1993; Jolley et al., 2013) and even certain emotional disorders (Desmet et al., 2021; Nolazco-Flores et al., 2021), or simply be used to measure learning difficulties and creativity (Lee and Hobson, 2006; Urban, 2004). New technologies combined with new mathematical
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methods appear to be very useful and provide new possibilities to test mental states, intentions and emotions beyond these representations (Watanabe & Kuczaj, 2012). However, the meaning of each dimension has been assessed in visual terms only and is therefore not completely objective. New metrics could ultimately lead to the discover new cognitive dimensions and meanings, or reinforcing the discoveries of this study. Finally, the participants who have drawn for this study are all from France. To make these results universal, it could be useful to collect drawings from around the world.

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Authors’ Contribution  MP and CS supervised the study. MP and LM collected data. LM, BB and CS analysed data. CS wrote a first draft. All authors worked on the paper and approved the final version.

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Data Availability  The datasets generated during and/or analysed during the current study are available in the Zenodo repository, https://doi.org/10.5281/zenodo.5387520.

Declarations

Conflicts of Interest  The authors declare having no conflicts of interest.

Ethics Approval  The study was approved by the research ethical committee of Strasbourg University (Unistra/CER/2019-11).

Consent to Participate  Informed consent was obtained from all adult participants and from a parent or legal guardian for children. Informed consent for publication of identifying images in an online open-access publication has been obtained too.

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Cédric Sueur is a professor and member of the Institut Universitaire de France. Cédric Sueur is an ethologist and primatologist, in charge of the Master in Animal Ethics and co-responsible for the Master in Ecology, Eco-physiology and Ethology. Cédric Sueur is working on behavioral complexity in humans and non-human species. He is head of an international research laboratory between Strasbourg University and Kyoto University.

Lison Martinet is a young researcher working on the development of drawing’s behavior with an ontogenic point of view in humans and an evolutionary point of view by comparing great apes and human productions. She is studying drawings done by great apes like chimpanzees and by humans in developing news methods of analysis based on objective mathematical indices. For instance, these ones are based on fractals, space utilisation, the analysis of angles.

Benjamin Beltzung is a PhD student at the CNRS, and his current work focuses on drawings made by hominids (children from 2 to 10 years old, naive adults, experts’ adults, great apes) and the learning process linked to it, by using artificial intelligence. His doctoral project is interdisciplinary, as it requires behavioral biology, comparative psychology, mathematics and informatic. The main goal of his work is to develop deep learning algorithms to show differences at several levels: between orangutans, chimpanzees and humans; between humans (at different ages); between naive and experts’ adults.

Marie Pelé is a researcher in ethology, with a specialization in primatology. After obtaining a doctoral thesis on economic-type behaviors of several species of primates at the University of Strasbourg and postdoctoral experiences abroad, Marie Pelé created the Ethobiosciences expertise firm which allows her to carry out various scientific and educational missions, as well as counselling for animal professionals. In 2018, Marie Pelé returned to academia as a teacher at the University of Strasbourg. In 2020, she became a researcher in ethology at the Anthropo-Lab of the ETHICS laboratory of the Institut Catholique de Lille. She is developing a line of research dealing with human-animal relationships and behavioral strategies that could be implemented to improve them.

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