Making drawings speak through mathematical metrics

Cédric Sueur (✉ cedric.sueur@iphc.cnrs.fr)

Université de Strasbourg, CNRS, IPHC UMR 7178

Lison Martinet

Université de Strasbourg, CNRS, IPHC UMR 7178

Benjamin Beltzung

Université de Strasbourg, CNRS, IPHC UMR 7178

Marie Pelé

ETHICS EA7446, Lille Catholic University

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Abstract

Figurative drawing is a skill that takes time to learn, and 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 = 345) 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 colour 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. These analyses 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 have already discussed the perspectives of such findings in Comparative Psychology and Evolutionary Anthropology.

Introduction

Humans are the only species who naturally draw and paint objects. This behaviour takes time to develop over a series of childhood phases. Researchers agree that drawing evolves from scribbling in toddlers ^{1,2} to representational drawing in older children. In its initial phases, scribbling is often viewed purely as a motor pleasure that is not guided by visual planning, and is mainly determined by the mechanical functioning of the motor system of the arm, wrist and hand ^{2,3}. The youngest children show only transient interest in their own scribbles, and often readily move from one scribble to the next ^{4,5}. With increasing perceptual motor coordination and a progressive acquisition of complex and effective drawing rules, the scribbles become complex patterns that are guided by visual attention and are determined by aesthetic considerations such as balance or symmetry ^{4,6,7}. While a full-blown representational drawing (i.e. preplanned by the child and readable by an observer) first appears by the age of three to four years old ^{1,4,6,8}, preliminary indications of drawing-related symbolic actions can be traced back to as early as the second or third year of life. This finding suggests that at this age, children have already become aware of the dual function of a drawing, i.e. a graphic signifier that signifies a referent and is also a real object in its own right ⁹. Concerning the development of early mark-making and pre-representational activities, different theories have been developed, some of which are very similar ^{10–13}. The three following types of early pre-representations have been described in the literature, all of which were claimed to have appeared before children produce planned shapes: action representation, romancing, and guided elicitation ^{12,14}.

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 representation¹². The personal actions of children are therefore not random but are intentional and combined with marks and sounds to represent the moving, roaring object¹⁵⁻¹⁸. 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)). Romancing refers to instances where 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 questioning from 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. During these two stages, it is therefore difficult to establish if a drawing is goal-directed, with a meaning and an intentional representation. Evidence of intention is provided during the third step, called guided elicitation, when the child shows no representational intention in his free drawings but produces 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^{10,11,13,20}.

Different methods have been used to answer this question of representativeness and goal directedness beyond drawing^{21,22}. Publications describe topics ranging from the kinematic aspects of scribbling to the precursors of graphic representation, including authors who compare curved lines in drawings to mathematical laws. Children tended 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 finished drawing². However, these studies are not objective given that authors asked children *a posteriori* what their drawings represented. Moreover, this methodology cannot be applied to subjects (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 primates¹⁹.

This paper describes the use of different mathematical metrics to objectively and quantitatively measure intention and representativeness in drawing. Recently developed techniques make it possible to consider ethology as a physical science and apply quantitative measures in this discipline²³. Although simple drawing measures such as the number of colours can be used²⁴, 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 behavioural sequences are complex and predictable in animals, including humans. For instance, Martinet et al. (2021) and²⁵ used spatial and temporal fractal analyses, which had previously been applied to

understand optimal movements and optimal behavioural sequences of animals searching for food ^{26–29}, and found an increase in complexity and efficiency in humans compared to chimpanzees, but also an increase with age in humans. Other metrics such as entropy ^{30,31} or the Gini index ^{32,33} were also used to understand the distribution or complexity of different behaviours (e.g. activity, food exchange, vocalisation) 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 significant dimension, as already shown for personality ^{34,35} or sociality ³⁶. 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 or aestheticism in the drawing ^{18,37–39}. Temporal metrics and some spatial metrics based on fractal theory could indicate representativeness and anticipation, whilst the use of colours and space could indicate a sense of aestheticism. We used two datasets of drawings with different instructions in order to generalise results. We hypothesise 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.

Materials And Methods

a. Dataset

All methods were performed in accordance with the relevant guidelines and regulations in France, checked and approved by the research ethical committee of Strasbourg University (Unistra/CER/2019-11).

Dataset#1: We asked 13 adults (6 men, 7 women), aged from 21 to 29 years old, to draw five drawings. These adults were considered “naïve” insofar that 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: 1.) draw something with scribbles; 2.) draw something with circles; 3.) draw something with different angles; 4.) draw something with a starry sky; 5.) 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 in Section 2.c. Examples for each instruction are given in Figure 1. This dataset was collected in 2020 and is composed of 65 drawings.

Dataset#2: This dataset included children and adults. The group of 144 children aged from three to ten years old 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. The adult group was composed of 41 adults (21 men, 20 women) aged 21 to 60 years old who were naive and expert drawers. The latter were art school students and professional illustrators. Participation was voluntary for adults and subject to parental consent for children.

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 were initially collected for this dataset; however, some data were lost during the recording processes. The final dataset therefore contains 344 drawings. It should be noted that three of the naive subjects are present in both #dataset1 and #dataset2.

b. Experimental design

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

Habituation phase: each participant was invited to try a touchscreen tablet (iPad Pro, 13-Inch, version 11.2.2, capacitive screen reacting to the conductive touch of human fingers), and draw on it with their fingers to understand how it worked and how to change the colour they used to draw. Drawing with fingers was preferred in order to involve very young children who had not yet mastered the use of a pencil. A panel consisting of ten different colours was displayed at the bottom of the screen, and the participant could select a colour for their drawing by clicking on it. When they clicked on a different colour in the panel, any subsequent drawing production was in that colour. Children were habituated to the touchscreens the day before the tests to avoid overstimulation. Adults were tested immediately after discovering the tablet.

Testing phase: each child was individually tested during school time at school, located in their classroom (for the 3-year-olds) and in the staff room for the older children. The experimenter (LM or MP) stayed during the test but kept her distance during drawing 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.

c. Data analysis

For each drawing, the software developed for these studies (details and software available on demand), allowed us to record the spatial coordinates X and Y of every point of the lines drawn as well as their time coordinates [min; s; ms] and the colour used. This data collection allows us to calculate spatial, temporal and colour metrics per drawing (Table 1). Details of metrics, their calculation and the range of values for each instruction for dataset#1 can be found in the supplementary information section. The number of sequences is correlated to the number of lines in the drawing. We retain the number of sequences as data, as temporal sequences can be analysed using the Hurst index and analysed in parallel with the duration of each sequence.

For dataset#1, we expect different values according to the instruction:

- 1.) The scribbles drawings are not expected to show sharp angles and straight lines, so we predict the observation of a small μ MLE (see 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 high. Finally, scribbles should have few colours.
- 2.) We expect that drawings with circles will not show sharp angles (but rather obtuse ones) or straight lines, so a small μ MLE and a small angle distribution metric are predicted. 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 colours used.
- 3.) We expect drawings with different angles to have large angle distributions as well as large distributions of lines lengths, meaning an intermediate μ MLE. 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 colours used.
- 4.) We expect drawings of a starry sky to contain different angles. We expect long distances between stars but short lines to draw stars, indicating a high μ MLE. The minimum convex polygon, the number of sequences and the drawing session duration should all be high. The number of colours should be low and the colours should be light unless the participants drew a dark sky.
- 5.) We expect drawings with fan patterns to have sharp angles and long lines. We have no prediction for the minimum convex polygon. Speed should be high given the findings of literature on fan patterns 2,24. 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 colours used.

d. Statistical analysis

As preliminary results, we analysed 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 realised when ANOVA or Kruskal-

Wallis tests were significant (the “TukeyHSD” function of the R base package and the “kruskalmc” function of the “pgirmess” package 58, respectively). Only differences with $p < 0.05$ were reported.

Analyses were carried out in three main steps using correlation analyses and principal component analyses: 1.) Analysis of dataset#1, 2.) analysis of dataset#2 following the same procedure as in step 1, 3.) a final combined analysis of dataset#1 and #2 in order to generalise our results.

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. 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 61,62 with Varimax rotation was then carried out using the R package ‘Psych’ 63,64. 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 maximise 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 inferior to 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 analysed the results.

Second step on dataset#2: We followed the procedure described for dataset#1.

Third step on dataset#1 and dataset#2: We compared the variables contributing to each of the three dimensions for dataset#1 and dataset#2. 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. These results were then compared to assess whether our procedure might be generalised 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.

All analyses were carried out using Rstudio 1.4.1103 65,66.

Results

Preliminary results on dataset#1: the details of tests and pairwise comparisons between instructions (dataset#1) for each metric are available in the supplementary material section. 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 lower in drawings composed of different angles than in fan pattern drawings. The number of colours 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 to the fan pattern instruction). The starry sky instruction is linked to a longer drawing distance compared to all other instructions except fan patterns, whilst 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 Figure 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, ten 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 Table S1, supplementary material), namely the angles 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 (μ MLE, drawing speed, Gini metric, entropy metric, drawing distance), Dimension 2 (minimum convex polygon, mean colorimetric profile, number of colours), 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, 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%). Like 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 (μ MLE, drawing speed, drawing distance, minimum convex polygon), Dimension 2 (mean colorimetric profile, number of colours), Dimension 3 (Hurst index, number of sequences, Gini metric, Entropy metric).

Third step on dataset#1 and dataset#2: Seven of the ten retained variables belong to the same dimension in the PCAs carried out for Dataset#1 and Dataset#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 Figure 3a-c. 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). Mann-Whitney tests showed that Dimension 1 differs between dataset#1 and dataset#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 ($w = 105$, $p = 0.152$) (Figure 4). Moreover, Figure 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).

Discussion

We used several mathematical metrics to characterise drawings and assess whether they can give cues about representativeness and intention. Principal component analyses helped us to organise 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 generalise our method of characterising 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 analyse 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 involve different drawing instructions proves to be the right protocol to obtain variations in each metric. The colours 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 colours is still high and two colour metrics (i.e. number of colours 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 colours variable is more a question of personal preference than characteristic of any representative process. Similarly, and contrary to what we expected, the angles 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^{29,41,42}. The scale used to analyse 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 non-representative 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 non-representative 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^{2,12,17}. Indeed, the minimum convex polygon was also shown to be high with scribbles or other non-representative drawings (see Figure 3), which indicates that this metric cannot be used to understand the cognitive processes underlying drawing. The Gini index and entropy index, both measured on temporal sequences of drawing, also belong to different dimensions in dataset#1 and dataset#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. However, 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 dataset#1 and dataset#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 index and entropy index are increasingly used in different studies, despite a continuing debate about their interpretability^{55,67,68}. Future works are required to assess their potential role in the domain of drawing and other behaviours. 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 dataset#1 and dataset#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 analyse 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 μ MLE (see Table 1 for definitions). In movement ecology, the drawing speed is a proxy of goal directedness, i.e. the intention of an animal to go to a specific place that it knows^{41,56,57,69}. 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 ± 0.37 compared to 0.56 ± 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 colour, and in both of these cases, drawing speed is linked to drawing distance. This is what we obtained in our results (Tables 2 & 3, Figure 3) with many participants colouring the starry sky blue or black. This adds detail without providing a better representativeness of the drawing. On the other hand, μ 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 μ MLE is high. We qualified these movements as a Lévy flight (or walk)^{29,70}. In our drawing study, a high μ MLE indicates an efficient drawing, i.e. it is representative, intentional and with few details (see Figure 3). It is easy to recognise 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, Dimension 1 can be named 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^{71,72}. In our case effectiveness is representativeness, whilst efficiency is representativeness combined with few details (i.e. optimality). Efficiency might be illustrated in a sketch^{73,74} and by emoticons^{75,76}. 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 colours 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.

The second PCA dimension is composed of the number of used colours and the mean colorimetric profile. Adding and diversifying colours facilitates the differentiation of objects in a drawing. When there are few details in a drawing, one colour is enough to identify the object but when more details are present, the use of colours makes it easier to identify the different objects. This principle can be observed in Figure 3a, for instance, with the drawings of the crab (one colour) and the house (different colours to identify the flowers, the car, the butterfly, etc.). Colours facilitate the visual perception of objects and materials in our environment^{77,78}. In our drawing datasets, this cognitive process is found to make drawings easier to interpret and increase their external representativeness. This second dimension can be named "diversity" to represent the diversity of colours 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 Figures 3b and 3c (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. Dimension 3 can be named "sequentiality". When the complexity of the drawing increases to make something representative, the number of sequences and the stochasticity increase.

Our study showed that we can identify three dimensions in drawing: efficiency, diversity and sequentiality. All three dimensions facilitate our understanding of drawing representativeness. This statement can be observed in Figure 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. 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). 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 representativeness²⁰. 3) Finally, the method can be extended to psychopathologies such as autism^{79,80} and even certain emotional disorders^{21,81}, or simply be used to measure learning difficulties and creativity^{22,82}. New technologies combined with new mathematical methods appear to be very useful and provide new possibilities to test mental states, intentions and emotions beyond these representations⁸³. 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.

Declarations

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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.

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.

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>

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Tables

Type	Metric	Definition	Meaning ('it measures') or expectation ('we expect')	References
Spatial metrics	μ MLE	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	40–43
	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).	44–46
	Angle distribution metric	PCA dimension based on the coefficients of the cubic survival function of angle distribution (from 0° to 180°)	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)	47–50
	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	51,52
Temporal metrics	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	53,54
	Temporal 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	32,33
	Entropy index	Measure of the temporal uncertainty of drawing	It measures the stochasticity or predictability of the drawing state. We expect a high entropy index to be linked to more representative drawing, including anticipation	30,31,55
	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	
	Number of sequences	Number of drawing and non-drawing	We expect a high number of sequences to give an idea about goal-oriented behaviours,	

		sequences during the test	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)	41,56,57
	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	
Colour metrics	Mean colorimetric profile	Mean distribution of intensity levels for the Red, Green, or Blue colours respectively and after removing the white (screen) colour on the parts covered by drawing	It measures the mean spectrum of colours used, from dark to light.	
	Standard deviation of the colorimetric profile	Standard deviation of the distribution of intensity levels for the Red, Green, or Blue colours respectively, on the parts covered by drawing	It measures the diversity of the spectrum of colours used. It is different from the number of colours as it takes also how much these colours are different.	
	Number of colours	Number of colours used from the ten proposed colours.	We expect the number of used colours to give an idea about the aestheticism but also inform about the play interest in drawing.	19

Table 1: Metrics used to understand drawing complexity with their definition and their meaning in the context of drawing.

	Dataset#1			Dataset#2		
	Dim. 1	Dim. 2	Dim. 3	Dim. 1	Dim. 2	Dim. 3
μ MLE	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
N° 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 colours profile	0.437	0.711	-0.191	-0.168	0.857	
Number of colours	0.11	0.759	-0.144	0.181	0.607	
Drawing distance	-0.754		0.223	0.708	-0.488	-0.296

Table 2: Loadings of the metrics (after loadings selection) on the three Varimax rotation PCA dimensions of dataset#1 and dataset2. Bold values indicate the dimension in which the metric is retained in each dataset. Grey highlights indicates similar results for both datasets. Axes of Dimension 1 are inversed between Dataset#1 and Dataset#2, but results and correlations are similar.

	Dataset#1			Dataset#2			Dataset#1 & #2		
	Dim. 1	Dim. 2	Dim. 3	Dim. 1	Dim. 2	Dim. 3	Dim. 1	Dim. 2	Dim. 3
μ MLE	0.812			0.814	-0.117	0.246	0.778	-0.14	0.252
Hurst index		0.248	0.872	-0.143		0.902			0.905
N° of sequences	-0.188	0.112	-0.886			-0.898			-0.896
Drawing speed	-0.894	-0.133		-0.9		-0.216	-0.88		-0.136
Mean colours profile	0.317	0.81		0.291	0.777		0.315	0.777	
N° of colours		0.909		-0.178	0.795		-0.141	0.824	
Drawing distance	-0.793	-0.194		-0.746	-0.371	0.296	-0.775	-0.312	0.21

Table 3: PCA loadings of the metrics similar to dataset#1 and dataset#2. Bold values indicate dimensions in which the metric is retained in each dataset.

Figures

Figure 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.

Figure 2

correlation chart of the 14 metrics for dataset#1. The diagonal of the graph provides the distribution of each metric, whilst the bottom left and the top-right provide the correlation figure and the correlation coefficient between two metrics, respectively. Statistical value is given with the correlation coefficient: * means $p < 0.05$, ** means $p < 0.01$, and *** means $p < 0.001$.

Figure 3

a: Examples of Dataset#1 (third step) drawings according to Dimension 1 and Dimension 2, as provided by the PCA. Dimension 1 may represent representativeness in drawing whilst Dimension 2 may represent diversity in drawings. b: Examples of Dataset#1 (third step) drawings according to Dimension 1 and Dimension 3, as provided by the PCA. Dimension 1 may represent representativeness in drawing whilst Dimension 3 may represent periodicity in drawings. c: Examples of Dataset#1 (third step) drawings according to Dimension 2 and Dimension 3, as provided by the PCA. Dimension 2 may represent diversity in drawing whilst Dimension 3 may represent periodicity in drawings.

Figure 4

Examples of scribbles for dataset#1 (adults) and dataset#2 (3-year-old children) and boxplot of dimensions 1 to 3 for these two categories.

Supplementary Files

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