Supporting information 1

Is the mean duration of chimpanzee sexual solicitation gesture types significantly small?

Following earlier work on chimpanzee play gestures (Heesen et al., 2019), we first calculated mean duration of all gesture types *L* via the equation:

$$L = \sum_{i=1}^{n} p_i e_i \qquad (1)$$

where *n* is the number of elements within the repertoire, p_i is the normalized probability of the i^{th} element – calculated by dividing the frequency of the i^{th} gesture by the total frequency of all gestures – and e_i is the magnitude of the i^{th} element (*i.e.*, its average duration *d*).

To test for compression and whether Zipf's law holds in chimpanzee sexual solicitation gestural communication, we used a permutation test assessing whether *L* was significantly small (Sokal & Rohlf, 1995). Following (Heesen et al., 2019) we created "*a control distribution of L (L') defined by a permutation function π (i)"* and calculated the left *p*-value by dividing the number of permutations where *L'≤L* by the number of total permutations, here 10^5. *L* was also calculated and tested for each subset created.

$$L' = \sum_{i=1}^{n} p_i e_{\pi(i)} \qquad (2)$$

Is the expected total sum of the duration of gestures of each sequence significantly small?

As explained by (Heesen et al., 2019), the total duration of a collection of sequences can be quantified as

$$M = \sum_{i=1}^{N} T_i \qquad (3)$$

where T_i is the total duration of the ith sequence and N is the number of sequences.

In turn,

$$T = \sum_{j=1}^{n_i} t_{ij} \qquad (4)$$

where t_{ij} is the duration of the jth element of the ith sequence and n_i is the size of the ith sequence. Given that the mean duration of gestures from the ith sequence can be expressed as $\left(t_{ij}\right)_i = \frac{T_i}{n_i}$, M can be defined as

$$M = \sum_{i=1}^{N} n_i \left(t_{ij}\right)_i \qquad (5)$$

M was calculated through this equation and was tested to assess whether it is significantly small. We performed a similar permutation test to that conducted to test for the significance of *L*, to check whether *M* was significantly small (Zipf, 1936). In such case, n_i has the role of p_i and $\left(t_{ij}\right)_i$ has the role of e_i in the test, with n_i and $\left(t_{ij}\right)_i$ remaining constant during the test.

Supporting information 2

Duration distribution analysis

Before performing the GLMM analysis we analysed the distribution of the gesture duration data by (1) visually inspecting its empirical density and cumulative distribution (Fig 1 in S2 File) and (2) assessing its skewness and kurtosis via the visual inspection of the Cullen and Frey graph (Fig 2 in S2 File). Fig 1 shows how the data is skewed towards low values, as almost half of the data lays between 0 and 3 seconds. Further, we fitted three theoretical distributions to the data - namely Weibull, Gamma and Lognormal – and compared loglikelihood values (Table 1 in S2 File). We then plotted the three distributions and visually inspected the Q-Q, P-P and histogram density plots (Fig 3 in S2 File). Finally, we compared Weibull, Gamma and Lognormal distributions against gesture duration data distribution via goodness-of-fit tests and goodness-of-fit information criterion (Table 2 and 3 in S2 File), which helped identify the lognormal distribution as the best fitting one. Therefore, we proceeded with log-transforming the duration variable to best fit model assumptions.

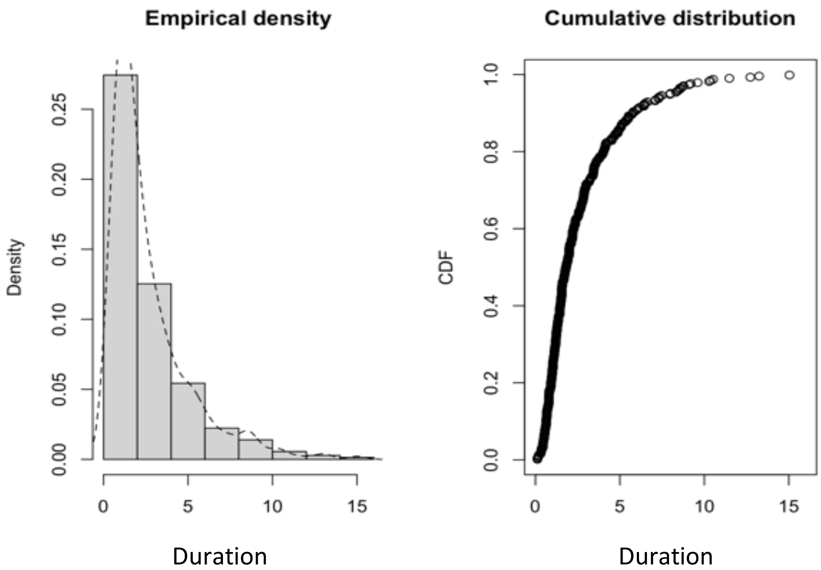


Fig 1. Empirical distribution of gesture duration.

Histogram and empirical cumulative distribution function (CDF) plots representing the distribution of gesture duration. Histogram bars represent sample distribution, dashed line indicates empirical density.

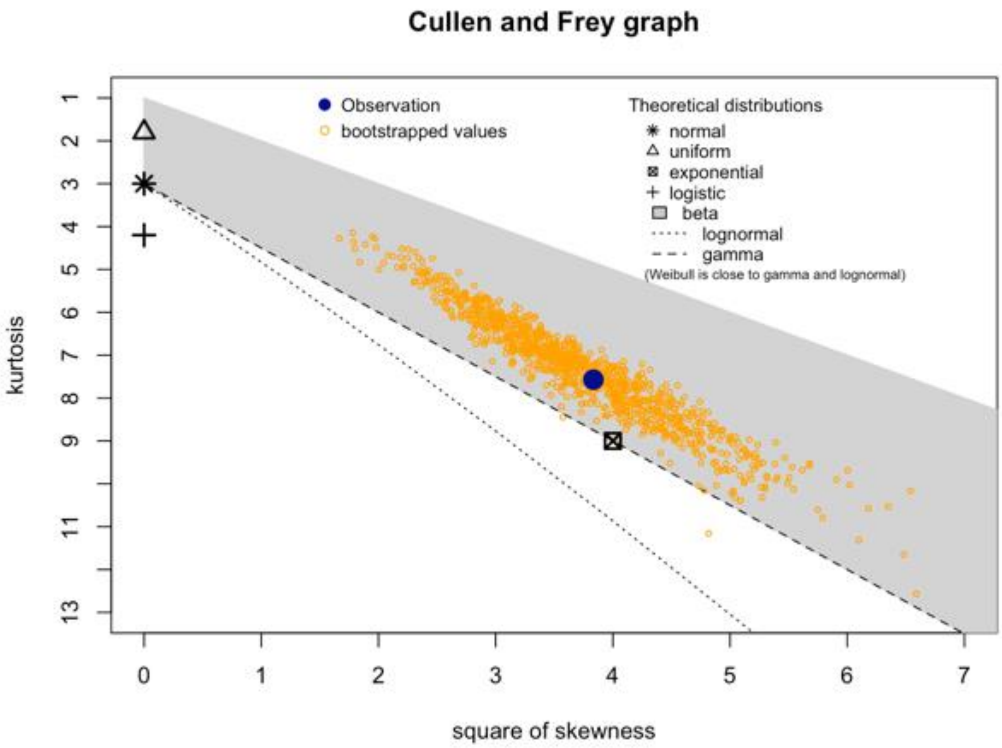


Fig 2. Cullen and Frey graph for gesture duration.

The graph depicts the distribution of the skewness and kurtosis of gesture duration data with bootstrapped values, plotted against other theoretical distributions, namely normal, uniform, exponential, logistic, beta, lognormal and gamma.

Table 1. Estimate and standard error for fitting the parameters of three theoretical distributions to the distribution of the gesture duration data.

Distribution	Parameters	Estimate	Std Error	Loglikelihood
Weibull	Shape	1.229711	0.04786805	-695.5846
	Scale	2.848181	0.12958597	
Gamma	Shape	1.5695397	0.10700744	-688.7789
	Rate	0.5933806	0.04755517	

Lognormal	meanlog	0.6214851	0.04530977	-677.7389
	sdlog	0.8584975	0.03203865	

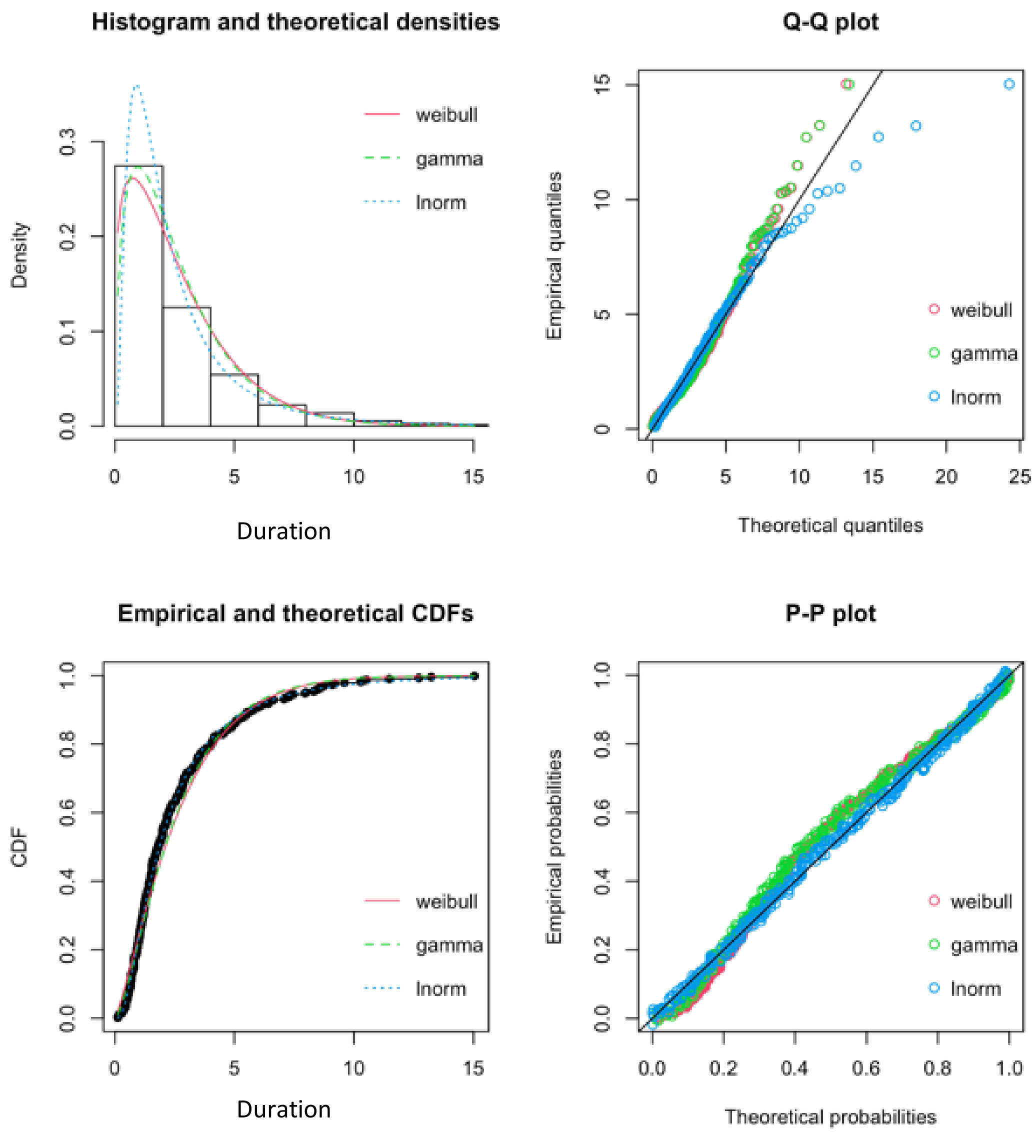


Fig 3. Histogram and theoretical densities, Q-Q and P-P plots depicting the gesture duration data distribution against the fitted Weibull, Gamma and Lognormal distributions. Histogram represents the distribution of duration data while the red, dashed green and dashed blue lines indicate the theoretical Weibull, gamma and lognormal distributions, respectively.

Table 2. Goodness-of-fit statistics compared across fitted distributions to the gesture duration data.

Goodness-of-fit statistics	Weibull	Gamma	Lognormal
Kolmogorov-Smirnov statistic	0. 07621865	0.08155393	0. 03242513
Cramer-von Mises statistic	0.62478933	0.55850079	0.03735280
Anderson-Darling statistic	3.88457421	3.08240994	0.30076490

Table 3. Goodness-of-fit information criteria compared across fitted distributions.

Goodness-of-fit criteria	Weibull	Gamma	Lognormal
Akaike's Information Criterion	1395.169	1381.558	1359.478
Bayesian Information Criterion	1402.936	1389.324	1367.244

Supporting information 3

Two-tailed results

Zipf's law of brevity

We did not find a pattern corresponding to Zipf's law of brevity, with no correlation between mean gesture type duration (*d*) and frequency of use (*f*) (Spearman correlation: r_s=0.30, *n*=26, *p*=0.131), which remained non-significant when excluding an outlier gesture type performed more than 250 times (Spearman correlation: r_s=0.22, *n*=25, *p*=0.293). When analysing only manual gestures, *f* and *d* tended to be significantly positively correlated (Spearman correlation: r_s=0.42, *n*=21, *p*=0.061). Conversely, we did not find any correlation between *f* and *d* in whole body gestures (Spearman correlation: r_s=-0.3, *n*=5, *p*=0.683).

Menzerath's law

We failed to find a pattern between sequence size *n* and mean constituent duration *t* of the same sequence that followed Menzerath's law (Spearman correlation: r_s=-0.08, *n*=376, *p*=0.142). When analysing sequences comprising only whole-body size and average gesture duration showed a significant positive correlation (Spearman correlation: r_s=0.59, *n*=20 *p*=0.005). Sequence size and average gesture duration did not correlate in sequences composed of only manual gestures (Spearman correlation: r_s=-0.06, *n*=315 *p*=0.324), or in those formed by both manual and body gestures (Spearman correlation: r_s=0.09, *n*=24 *p*=0.673).

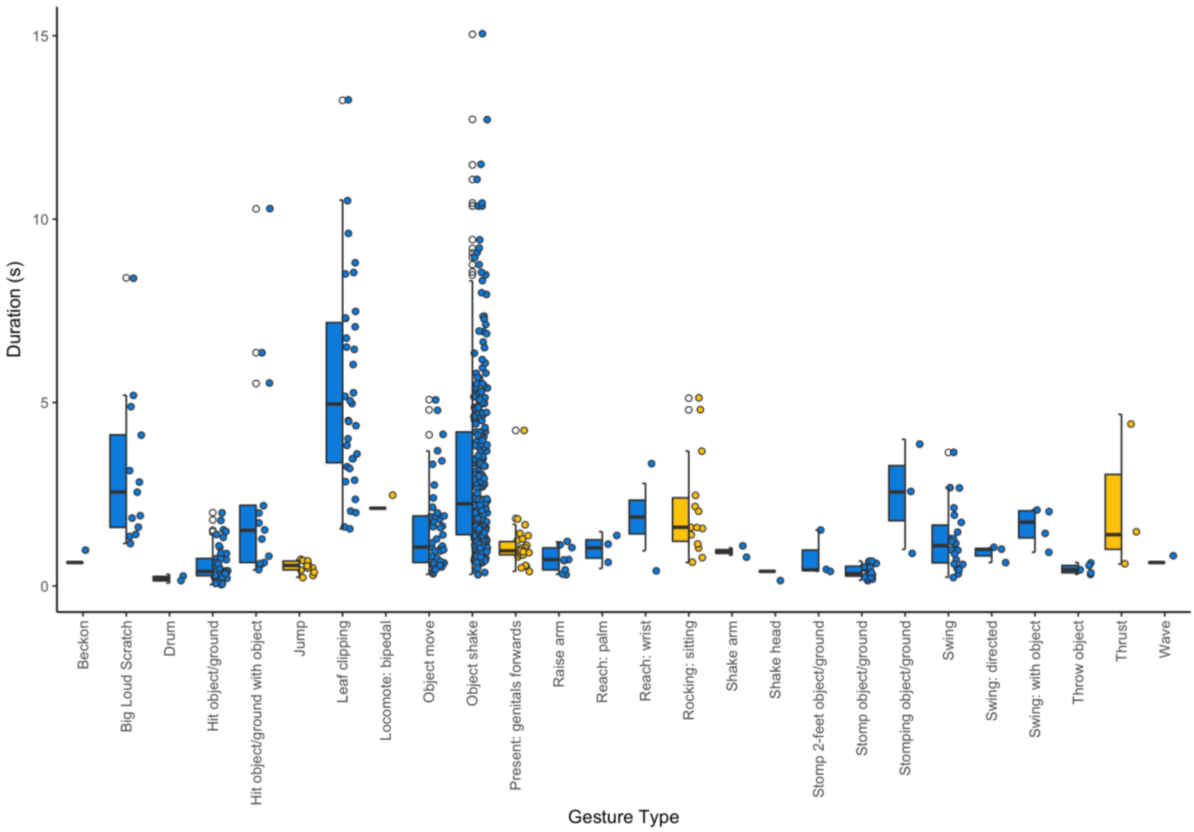
Supporting information 4

Ethogram of the 26 gesture types recorded in the dataset. Definitions are taken from (Hobaiter & Byrne, 2011a) and (Nishida, 2010).

Gesture	Description	Type
Beckon	Hand is moved in an upwards sweep from the elbow or wrist towards signaller.	Manual
Big loud scratch	Loud exaggerated scratching movement on the signaller’s own body.	Manual
Drum	Short hard audible contact of alternate palms against an object, usually tree roots.	Manual
Hit object/ground	Movement of whole arm, with short hard audible contact of closed fist to an object or the ground. Includes gestures performed with one and both arms.	Manual
Hit object/ground with object	As 'hit object/ground' but the signaller holds an object in the hand/hands, which contacts the ground.	Manual
Jump	While bipedal, both feet leave the ground simultaneously, accompanied by horizontal displacement through the air.	Body
Leaf clipping	Strips are torn from a leaf (or leaves) held in the hand using the teeth; produces a conspicuous sound.	Manual
Locomote: bipedal	The signaller walks bipedally while standing up.	Body
Object move	Object is displaced in one direction, contact is maintained throughout movement. Includes gestures performed with one or both hands.	Manual
Object shake	Repeated back and forth movement of an object, usually stem of shrub, branch of tree or woody vine, performed with either one or both hands.	Manual
Present: genitals forwards	Signaller shows genitals to recipient.	Body
Raise arm	Raise arm and/or hand vertically in the air and direct palm to companion.	Manual

Reach: palm	Arm extended to the recipient with the palm exposed. Typically held up or to the side, although very occasionally down. It is the palm or tip of the fingers that is closest to the recipient.	Manual
Reach: wrist	Arm extended to the recipient with the palm sheltered (fingers are curled), and it is either the wrist, or the back of the fingers that is reached out to the recipient.	Manual
Rocking: sitting	Slight or vigorous side to side movements of the body when the signaller is sitting.	Body
Shake arm	Small repeated shake (adduct or abduct) of horizontally-held arm at another. Includes gestures performed with either one or both arms.	Manual
Shake head	Small repeated back and forth motion of the head.	Body
Stomp 2-feet object/ground	As 'stomp object/ground' but performed with both feet.	Manual
Stomp object/ground	Sole of the foot is lifted vertically and brought into a short hard audible contact with the surface being stood upon (e.g., ground, branch).	Manual
Stomping object/ground	As 'stomp object/ground' but performed repeatedly.	Manual
Swing	Large back and forth movement of the arm held below the shoulder, or of leg from the hip. Includes gestures performed with one and two arms.	Manual
Swing: directed	As 'swing' but the direction of the swing indicates the direction of desired movement, immediately followed by the recipient moving as indicated.	Manual
Swing: with object	As 'swing' but the signaller holds an object in their hand/hands (e.g., branch, leaves, etc).	Manual
Throw object	Object is moved and released so that there is displacement through the air after the moment of release.	Manual
Thrust	Rhythmic back and forth movements of the pelvis.	Body
Wave	Large repeated back and forth movement of the arm raised above the shoulder.	Manual

Supporting information 5



S5 Fig. Distribution of gestural instances across the 26 gesture types detected with relative gesture duration. Boxplots represent the median (black bar), the interquartile range – IQR (boxes), maximum and minimum values excluding outliers (whiskers) and outliers (black dots). Points represent individual gestures. Whole-body gestures are indicated in yellow, manual gestures in blue.

Supporting information 6

Model 2 results

Results for the Model 2 GLMM analysis having response variable a subset of the gesture duration data which excluded all durations from the outlier gesture Object shake performed more than 250 times. No factor analysed had a significant impact on gesture duration

Table 1. GLMM results for Model 2.

			Confidence intervals	
Predictors	**Estimate ± SE**	***Parameter***	**Lower**	**Upper**
(Intercept)	0.39 ± 0.37	1.06	-0.33	1.12
Proportion[a]	-5.85 ± 5.12	-1.14	-15.82	4.23
Category[b]	-0.19 ± 0.37	-0.53	-0.91	0.53
Proportion *Category	5.96 ± 5.28	1.129	-4.48	16.23
Random effect				
σ^2	0.88			
$\tau_{00\ Signaller}$	0.20			
Number of individuals	16			

In Model 2 we tested for Zipf's law of brevity by fitting a Generalized Linear Mixed Model using 'lme4', assigning the response variable to gesture duration *d* for the subset of the data which excluded all durations from the outlier gesture Object shake, performed more than 250 times in the dataset. Into this we included [a]Proportion (Proportion of gesture type within the dataset), and [b]Category (manual or whole-body gesture types), and their interaction as fixed effects. We included Signaller ID as a random effect. For each predictor, parameter estimate and standard error (SE) are reported with standardised parameters (*Parameter=Estimate/SE*) and confidence intervals. We also report model random effect variance (σ^2) and between-individual variation ($\tau_{00\ Signaller}$).

As for Model 1, when ranking models based on their AIC score all the factors were included in the best-fitting model (Table 2). However, in contrast to Model 1, once the models were ranked based on their BIC value, which favours parsimonious model, none of the factors were included in the best-fitting model (Table 3).

Table 2. Model 2 ranking based on AIC values.

Model predictors	***df***	***AIC***	***Delta***	***Weight***
Proportion[a], Category[b], Proportion * Category	**6**	**823.3**	**0.00**	**0.503**
Proportion	4	825.2	1.86	0.199
Intercept only	3	825.2	1.92	0.192
Category, Proportion	5	827.7	4.43	0.055
Category	4	827.9	4.58	0.051

Listed above are the model predictors. Outcome variable is gesture duration, with Signaller ID as a random factor. For each predictor combination, we report degrees of freedom (*df*), AIC value, difference in AIC values with first ranking model (Delta), and the relative likelihood of the model (weight) (Burnham & Anderson, 2004). The best fit model is highlighted in bold. [a]Proportion = Proportion of gesture type within the dataset; [b]Category = Manual or whole-body gesture types.

Table 3. Model 2 ranking based on BIC values.

Fixed factors	***df***	***BIC***	***Delta***	***Weight***
Intercept only	**3**	**836.3**	**0.00**	**0.818**
Proportion[a]	4	839.9	3.62	0.134
Category[b]	4	842.6	6.35	0.034
Proportion, Category, Proportion *Category	6	845.4	9.14	0.008
Proportion, Category,	5	846.2	9.88	0.006

Listed above are the model predictors. Outcome variable is gesture duration, with Signaller ID as a random factor. For each predictor combination, we report degrees of freedom (*df*), BIC value, difference in BIC values with first ranking model (Delta), and the relative likelihood of the model (weight) (Burnham & Anderson, 2004). Best fit model is highlighted in bold. [a]Proportion = Proportion of gesture type within the dataset; [b]Category = Manual or whole-body gesture types.

Supporting information 7

Untransformed data GLMM results

Results for the GLMM analyses with the untransformed response variable gesture duration. Results for Model 1, 2 and 3 with untransformed data (Table 1, 2, 3) are all in line with the results for the analysis that used log-transformed gesture duration reported in the main paper.

Table 1. GLMM results for Model 1 with untransformed response variable.

			95% Confidence intervals	
Predictors	**Estimate ± SE**	**Parameter**	**Lower**	**Upper**
(Intercept)	1.84 ± 0.8	2.313	0.28	3.40
Proportion[a]	-15.92 ± 22.41	-0.711	-59.75	27.91
Category[b]	-0.17 ± 0.81	-0.204	-1.76	1.42
Proportion*Category	18.97 ± 22.41	0.847	-24.87	62.81
Random effect				
σ^2	5.07			
$\tau_{00\ Signaller}$	0.00			
Number of individuals	16			

With Model 1 we tested for Zipf's law of brevity by fitting a Generalized Linear Mixed Model using 'lme4', assigning the response variable to gesture duration *d*. Into this we included [a]Proportion (Proportion of gesture type within the dataset), and [b]Category (Manual or whole-body gesture types), and their interaction as fixed effects. We included Signaller ID as a random effect. For each predictor, parameter estimate and standard error (SE) are reported with standardised parameters (*Parameter=Estimate/SE*) and confidence intervals. We also report model random effect variance (σ^2) and between-individual variation ($\tau_{00\ Signaller}$).

Table 2. GLMM results for Model 2 with untransformed response variable.

			95% Confidence intervals	
Predictors	**Estimate ± SE**	**Parameter**	**Lower**	**Upper**
(Intercept)	2.35 ± 0.74	3.179	0.91	3.79
Proportion[a]	-15.21 ± 10.25	-1.483	-35.21	4.91
Category[b]	-0.24 ± 0.74	-0.325	-1.69	1.20
Proportion*Category	16.49 ± 10.57	1.560	-4.28	37.08
Random effect				
σ^2	3.53			
$\tau_{00\ \text{Signaller}}$	0.71			
Number of individuals	16			

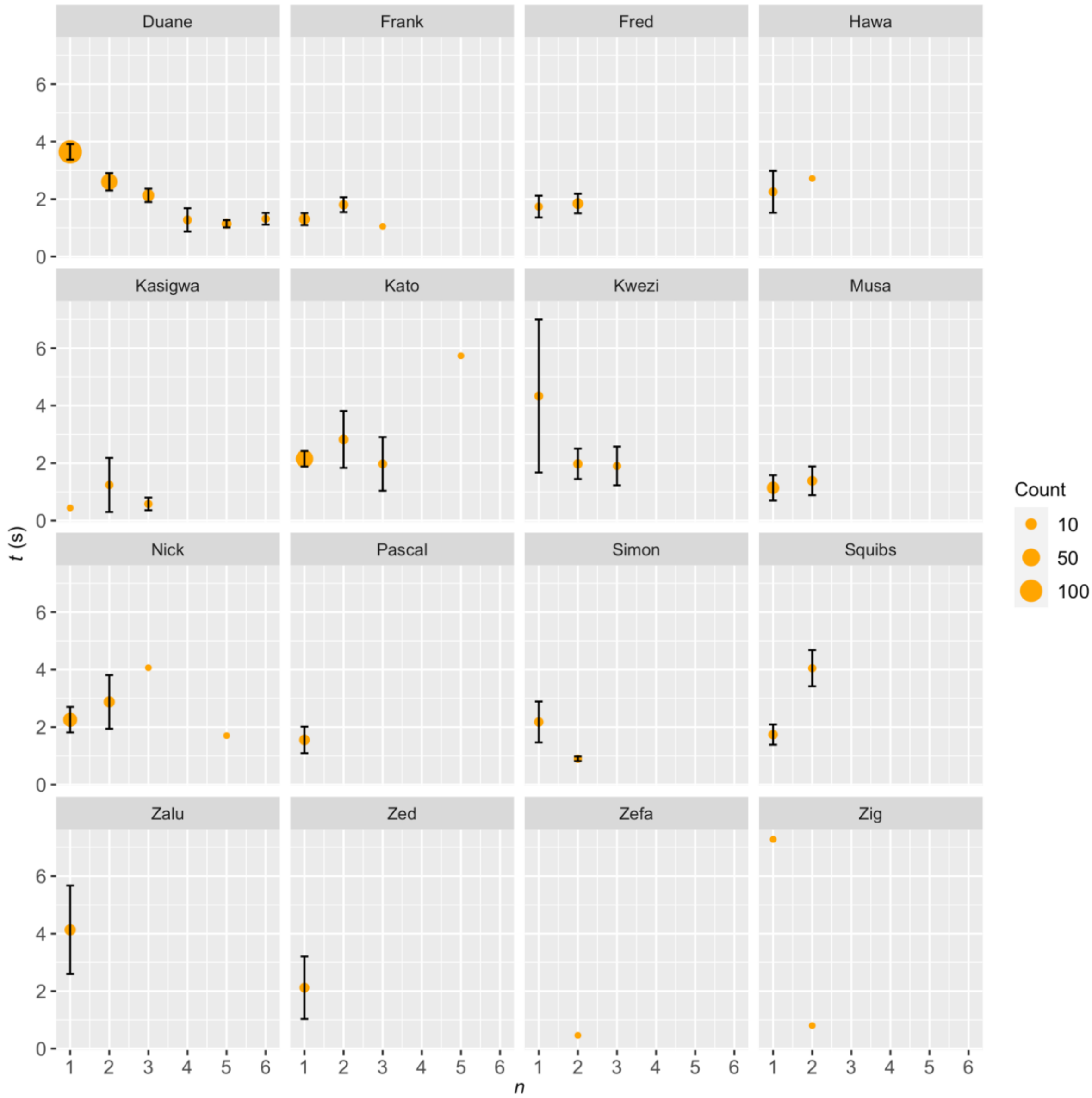
In Model 2 we tested for Zipf's law of brevity by fitting a Generalized Linear Mixed Model using 'lme4', assigning the response variable to gesture duration *d* for the subset of the data which excluded all durations from the outlier gesture Object shake, performed more than 250 times in the dataset. Into this we included [a]Proportion (Proportion of gesture type within the dataset), and [b]Category (Manual or whole-body gesture types), and their interaction as fixed effects. We included Signaller ID as a random effect. For each predictor, parameter estimate and standard error (SE) are reported with standardised parameters (*Parameter=Estimate/SE*) and confidence intervals. We also report model random effect variance (σ^2) and between-individual variation ($\tau_{00\ \text{Signaller}}$).

Table 3. GLMM results for Model 3 with untransformed data

			95% Confidence intervals	
Predictors	**Estimate ± SE**	**Parameter**	**Lower**	**Upper**
(Intercept)	3.14 ± 0.33	9.451	2.50	3.79
PWB[a]	-2.17 ± 1.17	-1.850	-4.45	0.16
Size[b]	**-0.45 ± 0.16**	**-2.820**	**-0.75**	**-0.13**
PWB*Size	0.59 ± 0.73	0.805	-0.86	2.01
Random effect				
σ^2	5.19			
$\tau_{00\ \text{Signaller}}$	0.38			
Number of individuals	16			

With Model 3 we tested for Menzerath's law by fitting a Generalized Linear Mixed Model using 'lme4', assigning the response variable to the average gesture duration *t* within the sequence. Into this we included [a]PWB (proportion of whole-body gesture types within a sequence) and [b]Size (number of tokens in a sequence), and their interaction as fixed effects. For each predictor, parameter estimate and standard error (SE) are reported with standardised parameters (*t=Estimate/SE*) and confidence intervals. We also report model random effect variance (σ^2) and between-individual variation ($\tau_{00\ \text{Signaller}}$). Significant results are highlighted in bold.

190 **Supporting information 8**



191 **S8 Fig. Relationship between sequence size *n* and average constituent gesture duration *t***

192 **for chimpanzee sexual solicitation gestural sequences based on individual identity.** Point

193 size indicates frequency of sequences with the same sequence size analysed in the dataset.

194

Supporting information 9

Menzerath's law in subset excluding the outlier individual Duane

No significant correlation was found between sequence size and average gesture duration in the sequence on the dataset which excluded gestural sequences performed by Duane (Spearman correlation: r_s=0.05, n=187, p=0.25). In agreement, M=558.43 and was not significantly small (p=0.601).

The GLMM analysis on the reduced dataset confirmed the absence of patterns in concordance with Menzerath's law, with no factor having an effect on average constituent duration (Table 1).

Table 1. GLMM results for the model testing Menzerath's law in a subset of the dataset.

			Confidence intervals	
Predictors	**Estimate ± SE**	**Parameter**	**Lower**	**Upper**
(Intercept)	0.35 ± 0.19	1.861	-0.02	0.71
PWB[a]	-0.70 ± 0.49	-1.428	-1.67	0.29
Size	0.07 ± 0.11	0.724	-0.12	0.27
PWB[a]*Size	0.24 ± 0.34	0.719	-0.42	0.89
Random effect				
σ^2	0.68			
$\tau_{00\ \text{Signaller}}$	0.12			
Number of individuals	15			

We tested for Menzerath's law by fitting a Generalized Linear Mixed Model using 'lme4', assigning the response variable to the average gesture duration t within the sequence but excluding data from the outlier individual *Duane.* Into this we included [a]PWB (proportion of whole-body gestures within a sequence) and Size (number of tokens in a sequence), and their interaction as fixed effects. For each predictor, parameter estimate and standard error (SE) are reported with standardised parameters (*t=Estimate/SE*) and confidence intervals. We also report model random effect variance (σ^2) and between-individual variation ($\tau_{00\ \mathrm{Signaller}}$). Significant results are highlighted in bold.