SUPPLEMENTARY MATERIALS

The perception of spontaneous and volitional laughter across 21 societies

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I. Demographic information and analysis

Table S1. Sex and age breakdown by study site.

Group	Region	N	Men	Women	Mean Age	Age SD	Age Range
S. Africa/Zulu	Africa	100	50	50	35	14.9	18-73
China	Asia	33	15	18	23.3	2.6	20-32
India	Asia	34	14	20	24.1	3	20-30
Indonesia	Asia	39	19	20	20.5	3.1	19-39
Iran	Asia	39	20	19	30	10	19-63
Japan	Asia	57	30	27	21.8	2.3	18-34
Korea	Asia	58	28	30	20.7	2	18-28
Qatar	Asia	31	0	31	22.4	2.4	19-27
Singapore	Asia	40	22	18	22.8	3.5	18-33
Samoa	Oceania	42	23	19	40.5	16.8	18-80
Australia	Oceania	32	18	14	28.8	13.4	19-72
Austria	Europe	29	8	21	30.5	6.7	22-48
Netherlands	Europe	43	25	18	23	2.3	18-27
Slovakia	Europe	71	13	58	24.4	7.4	18-60
Spain	Europe	35	18	17	22.8	4.1	18-33
Turkey	Europe	29	14	15	26.3	11.2	18-70
Canada	N. America	30	16	14	36.6	14.3	18-63
USA	N. America	48	16	32	19.4	2.6	18-24
Ecuador/Shuar	S. America	33	14	19	33.5	11.7	18-60
Peru (Urban)	S. America	30	9	21	21	2.5	18-27
Peru (Rural)	S. America	31	12	19	31.1	11	18-58
TOTALS	**6**	**884**	**384**	**500**	**26.6**	**7.0**	**18-80**

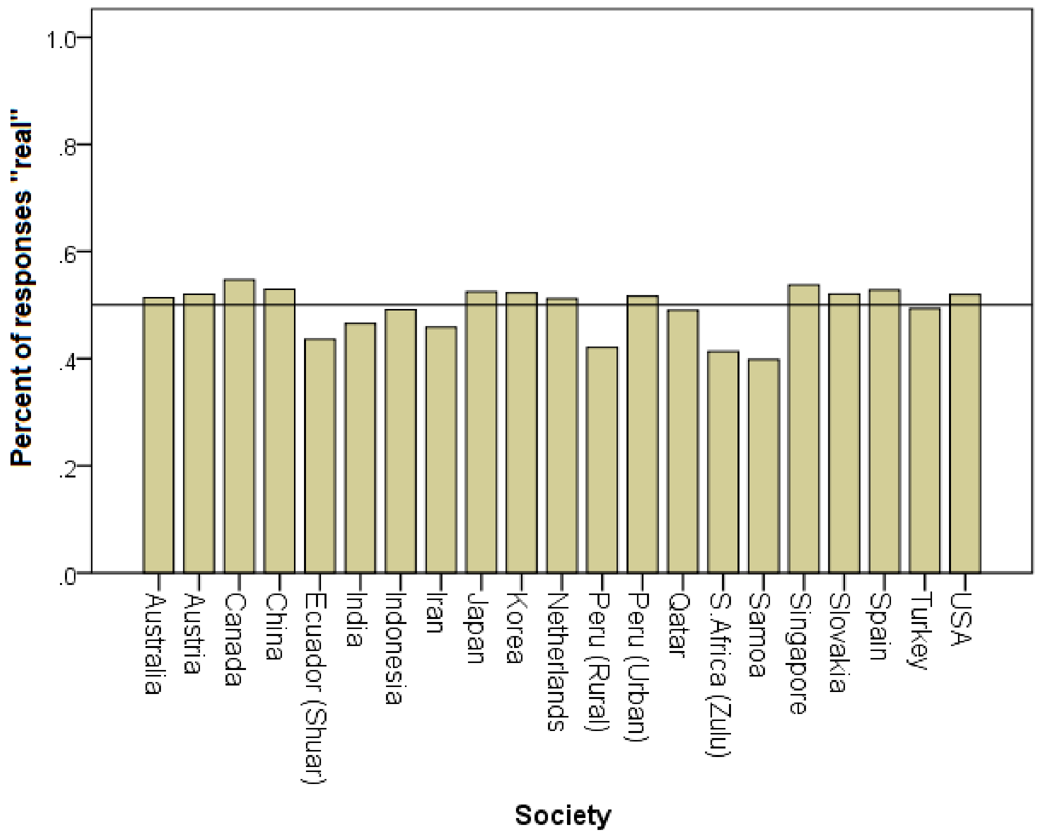
Table S2. Demographic information across 21 societies

Country Ethnic group	Participant's native language	Language in which experiment was conducted	Typical participant's English fluency	Mass media exposure	~% mass media in English	Typical participant's education	Community or city scale (number of people)	Economic mode(s) of participants
Australia	English	English	primary language	extensive	100	Some college	small towns (<5000) and large cities (>500000)	Industrial: low and highly skilled
Austria	German	German	moderate	extensive	50	Some college	small towns (<5000) and large cities (>500000)	Industrial: low and highly skilled
Canada	English	English	primary language	extensive	100	Some college	large cities	Industrial: low and highly skilled
China	Chinese	Chinese (Mandarin)	moderate	daily	50	Some college	large cities	Industrial: low and highly skilled
Ecuador/Shuar	Shuar	Spanish	none	minimal	<25	4-7 years	small villages (<200 people)	Hunting and gathering, small scale horticulture, agriculture, pastoralism, trade
India	Kannada	English	moderate	extensive	50	Some college	medium cities	Industrial: highly skilled
Indonesia	Jakartan	Formal Indonesian	moderate	extensive	75	8-12 years	large cities	Small-scale trade Industrial: low and highly skilled
Iran	Farsi	Farsi	minimal to moderate	extensive	25	College degree	large cities (>500000)	Skilled professional in office or institutional setting
Japan	Japanese	Japanese	minimal	daily	<25	8-12 years	large cities	Industrial: low and highly skilled
Korea	Korean	Korean	moderate	extensive	25	Some college	large cities	Small-scale: trade Industrial: low and highly skilled
Netherlands	Dutch	Dutch	fluent (as second language)	extensive	75	Some college	small and medium cities	Industrial: highly skilled
Peru (rural)	Spanish	Spanish	minimal	extensive	<25	8-12 years	small towns	Small-scale horticulture, agriculture, pastoralism Industrial: low skill
Peru (urban)	Spanish	Spanish	moderate	extensive	50	Some college	large cities	Industrial: highly skilled
Qatar	Arabic	Arabic	minimal	extensive	50	College degree	large cities	Industrial: low and highly skilled
Samoa	Samoan	Samoan	moderate	extensive	<50	8-12 years	large villages (200-1000) and small towns	Small-scale: trade Industrial: low and highly skilled
Singapore	English	English	primary language	extensive	75	Some college	large cities	Industrial: low and highly skilled
Slovakia	Slovak	Slovak	minimal	extensive	<25	College degree	large towns (5000-10000) and small cities	Industrial: highly skilled
South Africa/Zulu	isiZULU	isiZulu	minimal	occasional	<25	8-12 years	large villages (200-1000) and small towns	Small-scale agriculture, pastoralism, trade Industrial: low-skill
Spain	Spanish	Spanish	minimal	extensive	<25	Some college	small and medium cities	Industrial: low and highly skilled
Turkey	Turkish	Turkish	moderate	extensive	50	8-12 years	large cities	small scale trade industrial: low and highly skilled
USA	English,	English	primary language	extensive	100	some college	large cities	Industrial: low and highly skilled

Impact of demographic variables on response patterns

In any given trial, respondents decided whether the presented laugh was “real” or “fake.” The percent responding “real” are identifying the token as a spontaneous or real laugh. Across our samples, participants in societies that can be characterized as small-scale and/or rural tended to respond with “real” less than 50% of the time (i.e., biasing their responses toward “fake”). See Figure S1.

Figure S1. Responses of “real laugh” across 21 societies



For each study site, the respective researcher provided descriptive demographic information, including average levels of English fluency, exposure to mass media (both in any language, and the proportion of media in English), education, community scale (small villages to large cities), and the economic mode of the society (small-scale, traditional skills to industrialized, professional skills). As an exploratory analysis examining the possible role of population characteristics affecting judgments of laughter (using the same analytical method described in the main text), we modeled overall response patterns as a function of the six different demographic variables. We started with the best fitting model from the main analysis, and created six new models, each one adding only one demographic variable. Based on variance estimates for each demographic variable, and AIC comparison across models, economic mode was most associated with the pattern of responses. See Table S3. Figure S2 shows the pattern of responses of “real” across each demographic variable. There is a clear resemblance in each of these variables—higher overall rates of judging a laugh as “real” when originating from societies with higher rates of industrialization and professional skill. Because variation within study sites has been eliminated, care should be taken in interpreting demographic data of this kind (Kievit, Frankenhuis, Waldorp, & Borsboom, 2013). Nevertheless, these data do suggest that economic mode, community scale, and media exposure potentially play a role in shaping people's responses in our task, whereas familiarity with English appears less important.

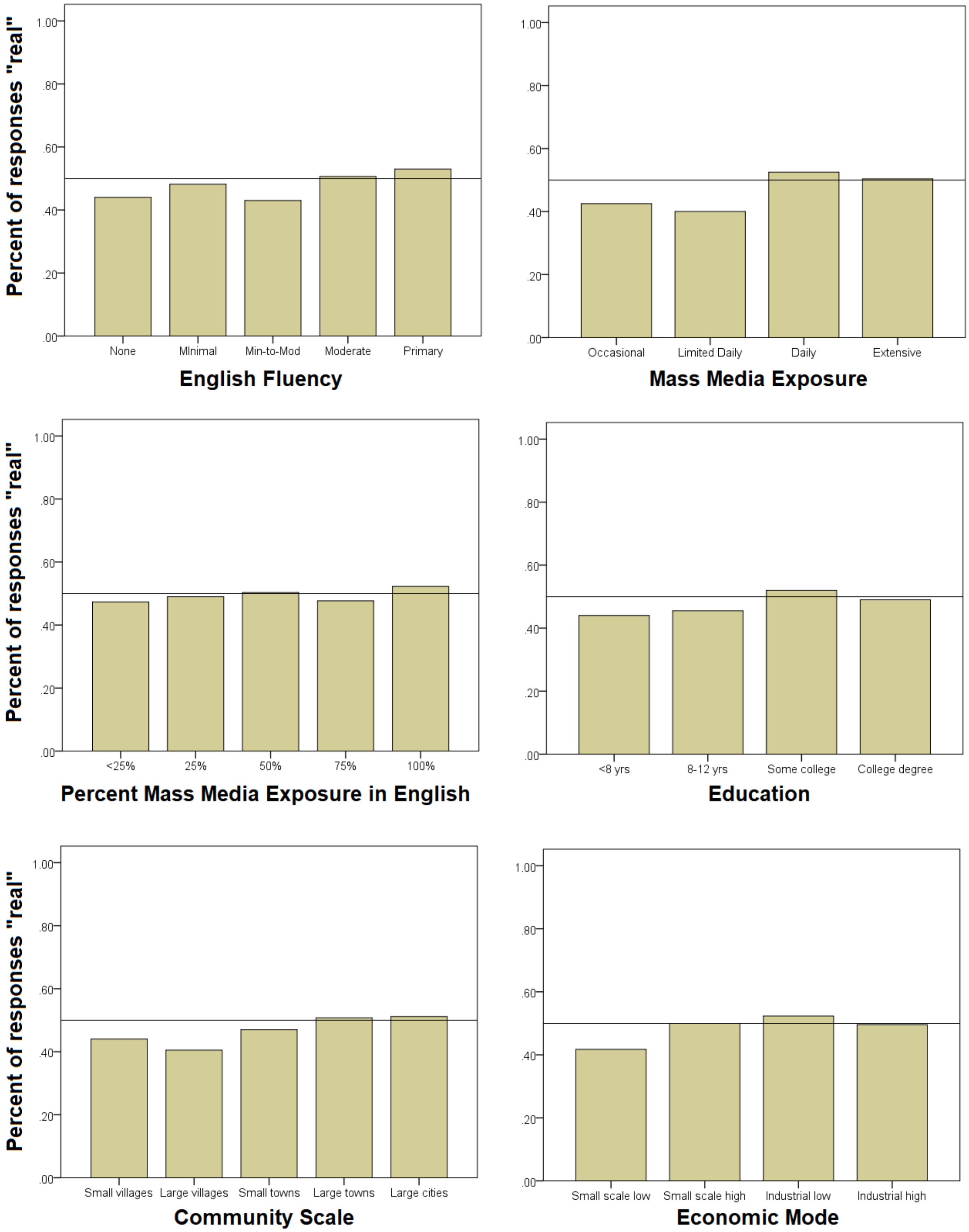
Table S3. Best-fit model of response patterns in judgments of "real" and "fake."

Random effects			**Fixed effects**				
Factor	***Variance***	***STD***	***Factor***	***Estimate***	***SE***	***z***	***Pr(>|z|)***
Subject	0.26071	0.5106					
Laugh Trial	1.95308	1.3975					
Society × Condition	0.04556	0.2135					
			(Intercept)	-0.7256	0.2738	-2.650	0.0080
			Condition	0.4161	0.2223	1.872	0.0612
			Econ mode2	0.4927	0.1393	3.538	0.0004
			Econ mode3	0.6172	0.1097	5.627	1.84e-08
			Econ mode4	0.4509	0.1218	3.702	0.0002

Participants from small-scale societies were more accurate assessing volitional laughs than spontaneous laughs, a pattern reversed in most of the other populations. This could reflect either greater skepticism regarding laughers' emotional engagement, or greater accuracy differentiating between spontaneous and volitional laughs. We labeled laughs produced in natural conversation between friends as spontaneous; however, some may actually have been volitional. In contrast, laughs labeled volitional were produced on command; a naïve undergraduate would be unlikely to produce a spontaneous laugh in such a context. Hence, it may be that, rather than being more skeptical, participants from small-scale societies were slightly more accurate. This pattern might reflect the greater importance in small-scale societies of deep and complex social relationships. In such a context, accurately judging another's degree of emotional engagement is critical in predicting behavior, hence listeners may be acutely attuned to indications of affective state. In contrast, large-scale societies have more relatively anonymous interactions in which the parties' respective behaviors are shaped primarily by roles in the social structure; such encounters are smoothed by the polite exchange of superficial tokens independent of genuine sentiment—potentially leading listeners to attend less closely to indices thereof.

Our stimuli suffer the limitations that i) some of our spontaneous laughs may actually be volitional, and ii) our volitional laughs were not produced in a social context, and thus may differ from more naturalistic volitional laughs. Taken together, these limitations indicate that our results may underestimate perceivers' discriminative ability because of added noise. Moreover, acoustic analyses identifying features of laughs associated with these eliciting conditions might not capture additional variation introduced by other possible eliciting conditions, such as non-interactive spontaneous laughs. Finally, it is important to note that the overall categorization of laughs as spontaneous, and spontaneous laughers as more aroused, are indirect as we did not directly collect measures from the laugh producers. These are important issues that future research should address.

Figure S2. Percent of responses “real” as a function of six demographic variables.



II. Acoustic Analysis and Signal Detection Analysis

Measures

Having demonstrated that participants could accurately judge whether laughs are spontaneous or volitional, we then measured a wide range of acoustic features of the laughter to identify which features would best explain the variance in participants' judgments. We examined the 36 laughs used in the experiment, 18 spontaneous and 18 volitional.

For each individual laugh within a given audio clip we measured the intervoicing intervals. We first calculated bout duration for each laugh from the onset of visible acoustic energy as viewed in a spectrogram (FFT method, window length: 0.005 s., time steps: 1000, frequency steps: 250, Gaussian window shape, dynamic range: 50 dB) to the offset of energy in the final call, or bout-final inspiratory element. Calls were counted based on audible and visible separated voiced energy. Mean intervoicing interval (IVI) was calculated as the summed lengths of all unvoiced intervals between calls (i.e., voiced call offset to voice call onset) divided by call number minus one. Unvoiced portions were determined by a lack of formant structure as viewed through a spectrogram with settings described above, and lack of periodicity with standard pitch range values. Finally, rate of IVI was calculated using the following formula:

$$\frac{\left(\frac{(\sum x_i)}{(c-1)}\right)}{\left(\frac{d}{c}\right)}$$

where x_i are the inter-voicing interval values, c is the total call number, and d is the bout duration of the series. This measure captures the averaged rate of unvoiced segments per call across a laugh bout.

Using Covarep (Degottex, 2014), we extracted fundamental frequency (F_0) (frequency range = 70-400 Hz), intensity, and harmonics-to-noise ratio of the laughs every 10 ms. F_0 values were converted to a logarithmic scale to approximate perceptual pitch. Per each of these measures, we calculated traditional descriptive statistics and (except for harmonics-to-noise ratio) temporal dynamics measures.

Descriptive statistics. We calculated: a) the total, voiced and unvoiced duration of each laugh, as well as the rate of intervoicing interval (IVI), b) the mean, standard deviation, median, interquartile range, coefficient of variation (standard deviation divided by the mean) and mean absolute deviation of pitch, intensity, and harmonics-to-noise ratio.

Temporal dynamics measures. Traditional descriptive statistics do not capture other crucial aspects of time-series properties such as their regularity over time and the temporal dependence between successive data points. These properties express the stability and complexity of voice production and have proven particularly useful to assess vocal behavior in a wide variety of contexts (e.g. Cummins et al., 2015; Fusaroli et al., 2016; Washington et al., 2012). To assess these temporal dynamics we employed two non-linear methods: a) Recurrence Quantification Analysis (RQA) of both voiced/unvoiced sequences and pitch (Marwan et al., 2007); and b)

Teager–Kaiser energy operator of pitch (TKEO) (Tsanas et al., 2012). RQA is a general non-linear time-series analysis tool that quantifies multiple aspects of temporal stability of a time series, such as how repetitive, noisy, or stationary it is.

Relying on the time series in each laugh (e.g., a sequence of estimated pitch regularly sampled over time), RQA reconstructs the phase space of possible combinations of states and quantifies the structure of recurrence; that is, the number of instances in which the time series displays repeated dynamics, and the characteristics of these repetitions. To apply RQA, two steps are necessary: 1) reconstructing the phase space underlying the time series, and 2) production of a recurrence plot. The phase space of a time series is an n-dimensional space in which all possible states of a system are represented, so that it is possible to portray the trajectories of the system's behavior, be it periodic (repeatedly crossing the same regions at regular intervals), random, or chaotic. To reconstruct the phase space, we applied a time-delay method to each time series. After reconstructing the phase space, we constructed recurrence plots for each time series. Black dots on the plots represent every occasion at which a phase space trajectory goes through approximately the same region in the phase space. In mathematical terms, if we represent the trajectory of a system as

$$\{\vec{x_i}\}_{i=1}^{N}$$

the corresponding recurrence plot is based on the following recurrence matrix:

$$R_{i,j} = \begin{cases} 1: \vec{x_i} \approx \vec{x_j}, \\ 0: \vec{x_i} \not\approx \vec{x_j}, \end{cases} i,j = 1, \ldots, N$$

where N is the number of considered states of the system and $\vec{x_i} \approx \vec{x_j}$ indicates that the two states are equal up to an error (or distance) ε. Note that this ε is essential in the case of continuous variables (as in F_0) as systems often do not recur exactly, but only approximately revisit states. To statistically analyze differences in laughs, we performed RQA on the recurrence plots. This makes it possible to statistically compare different dynamic systems (e.g., different dyads) in terms of such dynamics as the stability, structure, and complexity in the behavior of the system. Specifically, we analyzed:

Amount of repetition: The percentage of values that recur (are repeated) in the time series independently of the lag (recurrence rate, RR).

$$RR(\varepsilon) = \frac{1}{N^2} \Sigma_{i,j=1}^{N} R_{i,j}(\varepsilon)$$

Stability of repetition: articulated in:

Average length of sequences repeated (L)

$$L = \frac{\Sigma_{l=lmin}^{N} l\, P(l)}{\Sigma_{l=lmin}^{N} P(l)}$$

Length of longest repeated sequence (LMAX)

$$LMAX = \max(\{l_i\}_{i=1}^{N_l})$$

For more details about these indexes see Marwan et al. (2007).

TKEO has been widely employed to quantify jitter and shimmer; that is, perturbations in the regular cycles of pitch and intensity, respectively, which often characterize situations of stress and arousal, and are impacted by the ability to control the speech production system. TKEO is calculated as

$$\psi(x_n) = x_n^2 - x_{n+1} \cdot x_{n-1}$$

where the subscript *n* denotes the n^{th} entry of the vector *x* (in our case, the time series of pitch). We computed the mean, standard deviation and 5th, 25th, and 95th percentile values of TKEO.

Overall, this resulted in 39 features for each laugh.

Table S4. 39 extracted features in acoustic analysis.

Voiced / Unvoiced segments	**Pitch**	**Intensity**	**Harmonics to Noise Ratio (HNR)**
Total duration of the laugh	Pitch Mean	Intensity Mean	HNR Mean
Voiced duration	Pitch SD	Intensity SD	HNR SD
Unvoiced duration			
Mean intervoicing interval (IVI)	Pitch Median	Intensity Median	HNR Median
	Pitch IQR	Intensity IQR	HNR IQR
	Pitch CV	Intensity CV	HNR CV
	Pitch Mean Absolute Deviation	Intensity Mean Absolute Deviation	HNR Mean Absolute Deviation
	Recurrence Rate (RR)	Recurrence Rate (RR)	
	Mean length of recurrent sequence (L)	Mean length of recurrent sequence (L)	
	Maximum length of recurrent sequence (LMAX)	Maximum length of recurrent sequence (LMAX)	
	Mean TKEO	Mean TKEO	
	SD of TKEO	SD of TKEO	
	5^{th} percentile of TKEO	5^{th} percentile of TKEO	
	25^{th} percentile of TKEO	25^{th} percentile of TKEO	
	95^{th} percentile of TKEO	95^{th} percentile of TKEO	

This dataset was used to assess which acoustic features i) best discriminate between spontaneous and volitional laughs, and ii) might be employed by listeners when judging whether a laugh was spontaneous ("real") or volitional ("fake"). We call this measure the *Spontaneity Ratio* (SR), defined as the overall likelihood of each laugh being judged as spontaneous.

To examine cross-cultural reliability, we then employed the selected features to predict within-cultures SR and assessed the amount of variance explained through Adjusted R^2. All acoustic features were linearly transformed on a scale from 0 to 1 for better performance in the feature selection process.

Analysis and machine learning process

Feature selection. The process described above produces a large set of features, exemplifying what is commonly termed the curse of dimensionality. In other words, the presence of a large number of features makes the statistical models both difficult to interpret and at risk of overfitting, producing results that are not generalizable. To address this, we used a common algorithm to select a parsimonious subset of features, the Elastic Net extension of the LASSO (Zou & Hastie, 2005). In principle, this step could reduce overall accuracy, but it increases the interpretability and generalizability of the results; that is, the ability to accurately describe new laughs with characteristics similar to the laughs in the current study.

Statistical models. To assess the overall model relying on the selected features, we used a 5-fold cross-validated logistic regression to discriminate spontaneous versus volitional laughs, and a 5-fold cross-validated linear regression model to reconstruct participants' likelihood of judging a given laugh to be spontaneous (SR). The dataset was divided into 5 subsets (or folds) each containing a non-overlapping sixth of the laughs. A combination of 4 folds was used for feature selection and model fitting. The model was then assessed on the remaining fold. This procedure was repeated for all four possible combinations of folds, hence the accuracy of the model was assessed only on data on which it had not been trained. We repeated the cross-validation process a total of 100 times, randomly permuting the data before splitting into training and testing subsets to ensure stability of the results across different random splits in 5 folds. Post-hoc testing was applied to estimate Betas and standard errors of the predictors in the regression models.

Samoan judgments and acoustic-based model prediction. There is a notable divergence between the use of acoustic features by our Samoan participants and the other study populations. The acoustic-based model explained none of the variance in their responses, and alternative models using other acoustic features also failed to explain variance. Importantly, the inability of the model to explain Samoan's judgments of laughs being spontaneous does not suggest they use these features in some opposing way, but rather that they were likely relying on some other feature(s) not captured by our acoustic analysis. Across all societies, Samoan overall accuracy was the lowest (56%), and their rate of judging laughs as volitional was highest (60%). The finding deserves specific follow-up in future research.

Table S5. Variance (measured as r squared) in the judgments of laughs being spontaneous (i.e., "real") for each sample of participants explained by the acoustic-based model.

Group	**Region**	R^2
Australia	Oceania	0.62
Samoa	Oceania	0
South Africa/Zulu	Africa	0.48
Singapore	Asia	0.60
Korea	Asia	0.63
Japan	Asia	0.63
India	Asia	0.56
Iran	Asia	0.70
China	Asia	0.59
Indonesia	Asia	0.64
Qatar	Asia	0.70
Netherlands	Europe	0.64
Slovakia	Europe	0.66
Turkey	Europe	0.67
Spain	Europe	0.65
Austria	Europe	0.60
Canada	N. America	0.59
USA	N. America	0.64
Ecuador (Shuar)	S. America	0.24
Peru (urban)	S. America	0.66
Peru (rural)	S. America	0.54

Signal detection analysis

We performed a signal detection analysis in the form of a multilevel probit regression (DeCarlo, 1998). The binomial response (judgment of "real" versus "fake") was predicted by intercept (equivalent to criterion) and condition (spontaneous versus volitional laugh; equivalent to sensitivity). Both parameters were also modelled as random effects; that is, varying by society and participant, and as potentially correlated. The intercept indicates a bias in the responses—in particular, lower negative bias values indicate a greater tendency to respond "fake." Note that multilevel models perform partial pooling of information, so estimates of each society are influenced by the data available for all countries. This might reduce differences between societies, but it also provides more conservative estimates, and has been shown to improve generalizability of the models (Gelman & Hill, 2007). See Table S6 for all values.

To draw ROC curves by society, we estimated the predictions of the model above and employed them to assess the effects of varying decision thresholds on the sensitivity and specificity of the model binomial predictions.

Table S6. Signal detection values across 21 societies.

Society	Hit	False alarm	Correct rejection	Sensitivity	Bias	AUC
Australia	0.67	0.36	0.64	0.79	-0.37	0.68
Austria	0.69	0.35	0.65	0.87	-0.38	0.70
Canada	0.65	0.44	0.56	0.65	-0.27	0.65
China	0.67	0.39	0.61	0.77	-0.34	0.68
Ecuador (Shuar)	0.50	0.37	0.63	0.41	-0.38	0.64
India	0.56	0.37	0.63	0.53	-0.36	0.63
Indonesia	0.63	0.35	0.65	0.73	-0.39	0.66
Iran	0.59	0.32	0.68	0.68	-0.42	0.67
Japan	0.71	0.34	0.66	0.95	-0.40	0.71
Korea	0.71	0.34	0.66	0.94	-0.40	0.72
Netherlands	0.69	0.33	0.67	0.90	-0.40	0.71
Peru (Rural)	0.53	0.31	0.69	0.56	-0.44	0.65
Peru (Urban)	0.67	0.36	0.64	0.80	-0.37	0.68
Qatar	0.63	0.35	0.65	0.71	-0.38	0.68
S. Africa (Zulu)	0.51	0.31	0.69	0.52	-0.47	0.63
Samoa	0.46	0.36	0.66	0.36	-0.42	0.58
Singapore	0.66	0.42	0.58	0.68	-0.29	0.65
Slovakia	0.66	0.38	0.62	0.74	-0.33	0.67
Spain	0.68	0.38	0.63	0.81	-0.35	0.68
Turkey	0.66	0.32	0.68	0.85	-0.42	0.70
USA	0.69	0.35	0.65	0.89	-0.39	0.70

III. GLMM comparisons

We used a model comparison approach, assessing model fit using the Akaike Information Criterion (AIC). This approach allows researchers to assess which combination of variables best fit the pattern of data without comparison to a null model. Model 4 below (bolded) had the best fit, and is reported in the main text. The fit was almost identical to Model 6, the only difference being that Model 6 includes a non-significant sex difference in performance.

Table S7. Model comparisons for accuracy in the judgment task.

Model	Fixed factors	Random factors	Estimate	SE	z	Variance	SD	AIC
M1	(Intercept)		0.6001	0.2270	2.643			33814.2
	Condition		0.2298	0.1946	1.181			
		Subject				0.06618	0.2573	
		Laugh Trial				1.52421	1.2346	
M2	(Intercept)		0.5992	0.2326	2.576			33693.1
	Condition		0.2333	0.1965	1.187			
		Subject				0.02764	0.1662	
		Society				0.03930	0.1982	
		Laugh Trial				1.52717	1.2358	
M3	(Intercept)		0.57416	0.22870	2.511			33814.2
	Condition		0.23002	0.19498	1.180			
	Sex		0.04579	0.03216	1.424			
		Subject				0.06567	0.2563	
		Laugh Trial				1.52426	1.2346	
M4	**(Intercept)**		**0.6252**	**0.2389**	**2.617**			**33416.6**
	Condition		**0.1908**	**0.2188**	**0.872**			
		Subject				**0.03005**	**0.1733**	
		Society x Condition				**0.08939**	**0.2990**	
		Laugh Trial				**1.53619**	**1.2394**	
M5	(Intercept)		0.57607	0.23341	2.468			33693.3
	Condition		0.23340	0.19663	1.187			
	Sex		0.04057	0.03036	1.336			
		Subject				0.02728	0.1652	
		Society				0.03918	0.1979	
		Laugh Trial				1.52720	1.2358	
M6	(Intercept)		0.60190	0.23909	2.517			33416.9
	Condition		0.19096	0.21849	0.874			
	Sex		0.04092	0.03072	1.332			
		Subject				0.02968	0.1723	
		Society x Condition				0.08929	0.2988	
		Laugh Trial				1.53620	1.2394	
M7	(Intercept)		0.52005	0.23473	2.216			33686.9
	Condition		0.33952	0.20000	1.698			
	Sex		0.12550	0.04207	2.983			
	Condition x Sex		-0.15839	0.05434	-2.915			
		Subject				0.02735	0.1654	
		Society				0.03921	0.1980	
		Laugh Trial				1.53234	1.2379	

IV. Full text of experimental instructions

The following text was used in the experiment. If the participants did not speak English, these instructions were translated into the language to be used at the study site (usually the native language of the participants). If participants were unable to read, the instructions were read aloud to the participant and their answers entered into the computer by the experimenter.

Full text of instructions

Welcome to the fake-or-real laugh study. In this experiment you will listen to recordings of women laughing. In some of the recordings, the women were asked to laugh, but were not given any other reason for laughing (we call these fake laughs). Other recordings are of women laughing naturally while talking to a friend (we call these real laughs). For each recording, your job is to decide whether it is fake laugh or a real laugh. Each recording is of a different woman.

Before we begin with the actual study, you will be able to practice with one recording so that you will be familiar with the procedure.

When you are ready, press the space bar to hear the practice recording.

Do you think this laugh is a fake laugh or a real laugh?

Press 0 if you think that the laugh is fake. Press 1 if you think that the laugh is real.

If you have any questions, please ask the experimenter. If not, press the Enter key and the experiment will begin.

When you are ready, press the space bar to hear the recording.

You have now listened to all of the recordings. Thank you for your participation. Please tell the experimenter that you are finished.

V. Laughter samples

1. Spontaneous laugh 1 (spontaneous1.wav)
2. Sponatenous laugh 2 (spontaneous2.wav)
3. Volitional laugh 1 (volitional1.wav)
4. Volitional laugh 2 (volitional2.wav)

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