(Supplemental Material)

The shape of novel objects contributes to shared impressions.

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Appendixes

Appendix A

Here we provide further detail regarding our measures of impression-consistency and impression-consensus.

Study 1: Two methods for calculating impression-consensus

Table A1 shows the results of various tests for significance using two methods for calculating impression-consensus. None of the analyses were contradictory, however the estimated effect size differed between methods for calculating impression-consensus.

A1. Two methods for calculating impression-consensus (Study 1)

	Blocked Pairwise Correlation Correlations amongst all possible pairing of individuals per exposure.	Correlation with the Mean Correlations between individuals and the average reflecting all others.
Significance across all evaluations of objects	$t(39) = 6.67$, $p < .001$, $d = 1.06$, $r_M = .33$, $r_{SD} = .3$	$t(99) = 10.48$, $p < .001$, $d = 1.05$, $r_M = .55$, $r_{SD} = .52$
Significance across all evaluations of faces	$t(39) = 32.83$, $p < .001$, $d = 5.19$, $r_M = .26$, $r_{SD} = .05$	$t(87) = 27.46$, $p < .001$, $d = 2.93$, $r_M = .63$, $r_{SD} = .17$
Interaction Effect Between Stimuli and Evaluations	$F(3, 72) = 1003.4$, $p < .001$, $\eta_p^2 = .98$, $\eta^2 = .55$	$F(3, 180) = 40.69$, $p < .001$, $\eta_p^2 = .40$, $\eta^2 = .28$
Main Effect of Stimuli (between objects and faces)	$F(1, 72) = 272.8$, $p < .001$, $\eta_p^2 = .79$, $\eta^2 = .05$	$F(1, 180) = 12.80$, $p < .001$, $\eta_p^2 = .07$, $\eta^2 = .03$
Main Effect of Evaluation	$F(3, 72) = 716.8$, $p < .001$, $\eta_p^2 = .97$, $\eta^2 = .39$	$F(3, 180) = 40.42$, $p < .001$, $\eta_p^2 = .41$, $\eta^2 = .29$
Between Exposures for Objects	$F(9, 30) = .01$, $p = 1$, $\eta_p^2 = .00$, $\eta^2 = .00$	n/a because averages across blocks were first calculated
Between Exposures for Faces	$F(9, 30) = .20$, $p = .99$, $\eta_p^2 = .06$, $\eta^2 = .06$	n/a because averages across blocks were first calculated

Notes. Some analyses were not possible given the specific statistic; these cells are marked by 'n/a'. To test for the significance amongst the pairwise correlation, the analysis was executed per each exposure rather than using the averages across all the exposure blocks.

Study 1: Ten vs. two blocked exposures

Within the studies, significance testing used Fisher's *r* to *z* transformed scores. For the plots, the *z*-scores were transformed back to *r* coefficients. The transformations appear to inflate the correlation value; therefore, we report the correlation values at each stage of its transformation. We also report an analysis of impressions across 10 exposures and two exposures. It is debatable whether averages represent truer values because they decrease noise, or if they overinflate correlations while failing to represent any actual data point; therefore, we present both values.

Table A2 shows the impression-consistency for each condition. Impression-consistency across the 10 blocks was similar to the one found across the first 2 blocks.

A2. Impression-consistency: Faces & Novel Objects (Study 1)

	Pearson's *r*		Fisher's *r* to *z*		Fisher's *z* to *r*	
	Exposures 1-10	Exposures 1-2	Exposures 1-10	Exposures 1-2	Exposures 1-10	Exposures 1-2
Approach & Face	$r_M = .60$, $r_{SD} = .19$	$r_M = .51$, $r_{SD} = .18$	$z_M = .74$, $z_{SD} = .29$	$z_M = .59$, $z_{SD} = .25$	$r_M = .63$, $r_{SD} = .29$	$r_M = .53$, $r_{SD} = .24$
Danger & Face	$r_M = .47$, $r_{SD} = .24$	$r_M = .45$, $r_{SD} = .22$	$z_M = .56$, $z_{SD} = .34$	$z_M = .52$, $z_{SD} = .28$	$r_M = .51$, $r_{SD} = .33$	$r_M = .48$, $r_{SD} = .27$
Beauty & Face	$r_M = .59$, $r_{SD} = .21$	$r_M = .54$, $r_{SD} = .21$	$z_M = .74$, $z_{SD} = .33$	$z_M = .65$, $z_{SD} = .30$	$r_M = .63$, $r_{SD} = .32$	$r_M = .57$, $r_{SD} = .29$
Like & Face	$r_M = .59$, $r_{SD} = .23$	$r_M = .55$, $r_{SD} = .20$	$z_M = .73$, $z_{SD} = .32$	$z_M = .65$, $z_{SD} = .26$	$r_M = .62$, $r_{SD} = .31$	$r_M = .57$, $r_{SD} = .26$
Approach & Object	$r_M = .72$, $r_{SD} = .21$	$r_M = .75$, $r_{SD} = .10$	$z_M = 1.01$, $z_{SD} = .38$	$z_M = 1.02$, $z_{SD} = .22$	$r_M = .77$, $r_{SD} = .37$	$r_M = .77$, $r_{SD} = .21$
Danger & Object	$r_M = .77$, $r_{SD} = .11$	$r_M = .77$, $r_{SD} = .12$	$z_M = 1.08$, $z_{SD} = .27$	$z_M = 1.09$, $z_{SD} = .28$	$r_M = .79$, $r_{SD} = .26$	$r_M = .80$, $r_{SD} = .27$
Beauty & Object	$r_M = .58$, $r_{SD} = .22$	$r_M = .57$, $r_{SD} = .22$	$z_M = .72$, $z_{SD} = .33$	$z_M = .71$, $z_{SD} = .36$	$r_M = .62$, $r_{SD} = .32$	$r_M = .61$, $r_{SD} = .34$
Like & Object	$r_M = .58$, $r_{SD} = .21$	$r_M = .55$, $r_{SD} = .21$	$z_M = .72$, $z_{SD} = .34$	$z_M = .67$, $z_{SD} = .32$	$r_M = .62$, $r_{SD} = .33$	$r_M = .59$, $r_{SD} = .31$

Notes. Transformations from *r* to *z* occurred before averaging.

Table A3 shows the impression-consensus for each condition. Impression-consensus across the 10 blocks was similar to the one found across the first 2 blocks.

A3. Impression-consensus: Faces & Novel Objects (Study 1)

	Pearson's *r*		Fisher's *r* to *z*		Fisher's *z* to *r*	
	Exposures 1-10	Exposures 1-2	Exposures 1-10	Exposures 1-2	Exposures 1-10	Exposures 1-2
Approach & Face	r_M = .65, r_{SD} = .15	r_M = .57, r_{SD} = .19	z_M = .81, z_{SD} = .23	z_M = .68, z_{SD} = .26	r_M = .67, r_{SD} = .23	r_M = .59, r_{SD} = .25
Danger & Face	r_M = .58, r_{SD} = .22	r_M = .52, r_{SD} = .20	z_M = .72, z_{SD} = .32	z_M = .62, z_{SD} = .27	r_M = .62, r_{SD} = .31	r_M = .55, r_{SD} = .27
Beauty & Face	r_M = .68, r_{SD} = .13	r_M = .61, r_{SD} = .15	z_M = .87, z_{SD} = .23	z_M = .73, z_{SD} = .21	r_M = .70, r_{SD} = .23	r_M = .62, r_{SD} = .21
Like & Face	r_M = .60, r_{SD} = .17	r_M = .54, r_{SD} = .17	z_M = .74, z_{SD} = .28	z_M = .63, z_{SD} = .23	r_M = .63, r_{SD} = .27	r_M = .56, r_{SD} = .23
Approach & Object	r_M = .85, r_{SD} = .35	r_M = .72, r_{SD} = .47	z_M = 1.62, z_{SD} = .69	z_M = 1.16, z_{SD} = .83	r_M = .92, r_{SD} = .60	r_M = .82, r_{SD} = .68
Danger & Object	r_M = .94, r_{SD} = .04	r_M = .89, r_{SD} = .05	z_M = 1.83, z_{SD} = .32	z_M = 1.49, z_{SD} = .26	r_M = .95, r_{SD} = .31	r_M = .90, r_{SD} = .26
Beauty & Object	r_M = .03, r_{SD} = .20	r_M = .05, r_{SD} = .29	z_M = .04, z_{SD} = .21	z_M = .05, z_{SD} = .30	r_M = .04, r_{SD} = .21	r_M = .05, r_{SD} = .29
Like & Object	r_M = .38, r_{SD} = .62	r_M = .34, r_{SD} = .56	z_M = .52, z_{SD} = .91	z_M = .43, z_{SD} = .73	r_M = .48, r_{SD} = .72	r_M = .40, r_{SD} = .62

Notes. Transformations from *r* to *z* occurred before averaging.

Table A4 compares the level of impression-consensus between each condition. On the left, three methods of calculating consensus are reported: pairwise correlations computed upon each block ("Blocked Pairwise Correlation"), pairwise correlation using the averaged ratings across the ten blocks ("Pairwise Correlation"), and correlations with the mean. On the right, we compare each condition to test the significance of their difference using the values generated from the "correlation with the mean" method. The arrows point towards the condition yielding significantly more consensus.

A4. Impression-consensus compared across conditions (Study 1)

Blocked Pairwise Correlation	Pairwise Correlation	Correlation with the Mean		Approach & Face	Danger & Face	Beauty & Face	Like & Face	Approach & Object	Danger & Object	Beauty & Object
$r_{M} = .29$, $r_{SD} = .01$	$r_{M} = .44$	$r_{M} = .65$, $r_{SD} = .15$	Approach & Face							
$r_{M} = .20$, $r_{SD} = .03$	$r_{M} = .36$	$r_{M} = .58$, $r_{SD} = .22$	Danger & Face	• $p = 1$						
$r_{M} = .31$, $r_{SD} = .02$	$r_{M} = .49$	$r_{M} = .68$, $r_{SD} = .13$	Beauty & Face	• $p = 1$	• $p = 1$					
$r_{M} = .25$, $r_{SD} = .01$	$r_{M} = .39$	$r_{M} = .60$, $r_{SD} = .17$	Like & Face	• $p = 1$	• $p = 1$	• $p = 1$				
$r_{M} = .54$, $r_{SD} = .05$	$r_{M} = .72$	$r_{M} = .85$, $r_{SD} = .35$	Approach & Object	← $p < .001$	← $p < .001$	← $p < .001$	← $p < .001$			
$r_{M} = .70$, $r_{SD} = .02$	$r_{M} = .89$	$r_{M} = .94$, $r_{SD} = .04$	Danger & Object	← $p < .001$	← $p < .001$	← $p < .001$	← $p < .001$	• $p = 1$		
$r_{M} = .00$, $r_{SD} = .00$	$r_{M} = .00$	$r_{M} = .03$, $r_{SD} = .20$	Beauty & Object	↑ $p < .001$	↑ $p < .001$	↑ $p < .001$	↑ $p < .001$	↑ $p < .001$	↑ $p < .001$	
$r_{M} = .08$, $r_{SD} = .02$	$r_{M} = .15$	$r_{M} = .17$, $r_{SD} = .62$	Like & Object	• $p = .31$	• $p = 1$	• $p = .18$	• $p = 1$	↑ $p < .001$	↑ $p < .001$	← $p = .006$

Notes. Significant testing was executed using Fisher's *r* to *z* transformations on the correlations with the mean method; the other method does not allow for this level of analysis. If there was a significant difference, an arrow marks the variable associated with the greater consensus. The standard deviation for the blocked pairwise consensus represents differences in consensus across ten blocks. Whereas pairwise correlations averages across the ten blocks before calculating pairwise correlations; this later method does not provide an interpretable standard deviation statistic. The standard deviation for the correlation with the mean represents the differences between participants using impressions averaged over ten blocks.

Study 2: Impression-consensus

Table A5 shows the level of impression-consensus from different methods of calculation and across transformations from Pearson's *r* coefficients to Fisher's *z* and back to Pearson's *r*. Again, three measures of consensus are reported: pairwise correlations computed upon each block ("Blocked Pairwise Correlation"), pairwise correlation using the averaged ratings across the two blocks ("Pairwise Correlation"), and correlations with the mean. Averages are reported. For the *r* to *z* values, averaging was done after this transformation. The resulting *z* scores were then transformed back into *r* coefficients. These transformed scores are only possible using the "Blocked Pairwise Correlation" method and the "Correlation with the Mean" method because they generate more than value per condition.

A5. Impression-consensus: Evaluation & Shape (Study 2)										
	Blocked Pairwise Correlation				Pairwise Correlation		Correlation with the Mean			
	**N*	*r*	*r*→ *z*	*r*→*z*→*r*	*N*	*r*	*N*	*r*	*r*→*z*	*r*→*z*→*r*
Danger	14				1		18			
Family-X		.68	.82	.68	8	.80		.89	1.57	.92
Family-Y		.17	.17	.17		.30		.53	.74	.63
Family-Z		.13	.13	.13		.11		.31	.45	.43
Beauty	19				2		20			
Family-X		.00	.00	.00	0	.03		-	-.02	-.02
Family-Y		.30	.31	.30		.38		.01	.83	.68
Family-Z		.16	.16	.16		.19		.60	.57	.52
								.42		

Notes. Data regarding the images generated using the new renderer; 30 per shape-family. Means are reported. **N* for Blocked Pairwise Correlation excludes four participants from the dangerous condition and one participant's data from the beautiful condition due to an absence of observed variance across their impressions from a single block. The block which lacked variance occurred twice as the first block and three times as the second block amongst these five excluded participants.

Table A6 compares the level of impression-consensus between each condition for study-2.

A6. Impression-consensus compared across conditions (Study 2)					
	Danger & *Family-X*	Danger & *Family-Y*	Danger & *Family-Z*	Beauty & *Family-X*	Beauty & *Family-Y*
Danger & *Family-Y*	↑ $p < .001$				
Danger & *Family-Z*	↑ $p < .001$	• $p = .57$			
Beauty & *Family-X*	**↑ $p < .001$**	↑ $p < .001$	• $p = .05$		
Beauty & *Family-Y*	↑ $p < .001$	**• $p = 1$**	• $p = .20$	← $p < .001$	
Beauty & *Family-Z*	↑ $p < .001$	• $p = 1$	**• $p = 1$**	← $p < .01$	• $p = .57$

Notes. Significant testing was executed using Fisher's *r* to *z* transformations on the correlations with the mean method; the other method does not allow for this level of analysis. If there was a significant difference, an arrow marks the variable associated with the greater consensus. Comparisons between different evaluations of the same shape-family are highlighted in black.

Appendix B

Here we provide the regression tables for the models in which shapes predict impressions. **Table A7** shows the results of study-1, and **Table A8** shows the results of study-2. Separate mixed-effects models were made for each condition which yielded a significant level of impression-consensus.

A7. Regressing Impressions upon Shape-Parameters (Study 1)

	N	R^2	β	*SE*	*t*	*SD*
Approach	25	.74				
Fixed Effects		.54				
Intercept			4.56	.18	25.48	
Points			-.55***	.03	20.95	
Flux			-1.17***	.03	43.13	
Points:Flux			-.24***	.03	9.01	
Random Effects		.20				
Participants						.89
Residual						1.04
Danger	25	.86				
Fixed Effects		.66				
Intercept			4.96	.20	24.54	
Points			.41***	.02	18.82	
Flux			1.60***	.02	71.73	
Points:Flux			.29***	.02	12.93	
Random Effects		.20				
Participants						1.00
Residual						.85
Like	25	.18				
Fixed Effects		.10				
Intercept			4.79	.11	43.49	
Points			-.08*	.04	2.05	
Flux			-.46***	.04	11.10	
Points:Flux			-.16***	.04	3.89	
Random Effects		.08				
Participants						.51
Residual						1.58

Notes. b = Raw regression coefficients coefficient. *SE* = Standard Error for β. ' : ' denotes an interaction effect. Analysis using R packages: lme4 (1.1-12), lmerTest (2.0-32), & MuMIn (1.15.6). ****p* < .001, **p* < .05

A8. Regressing Impressions upon Shape-Parameters (Study 2)

	N	R^2	β	*SE*	*t*	*SD*

Danger & *Family-X*	18	.80				
Fixed Effects (shape-parameters)		.53				
Intercept			5.00	.30	16.42	
Points			.51***	.05	10.26	
Flux			1.57***	.05	30.26	
Points:Flux			.13***	.05	2.53	
Random Effects		.27				
Participants						1.27
Residual						1.09
Danger & *Family-Y*	18	.61				
Fixed Effects (shape-parameters)		.15				
Intercept			2.34	.25	9.34	
Points			-.18*	.08	-2.33	
Flux			-.18*	.08	-2.18	
Radius			-.35***	.07	-4.71	
Length			.03	.08	.33	
Points:Flux			.01	.08	.08	
Points:Radius			-.08	.11	-.71	
Flux:Radius			.38***	.10	3.74	
Points:Length			-.22*	.10	-2.19	
Flux:Length			.44***	.13	3.42	
Radius:Length			-.46***	.09	-5.31	
Points:Flux:Radius			.24	.12	1.96	
Points:Flux:Length			-.05	.13	-.42	
Points:Radius:Length			-.38*	.15	-2.50	
Flux:Radius:Length			.06	.11	.53	
Points:Flux:Radius:Length			.15	.14	1.01	
Random Effects		.46				
Participants						1.02
Residual						.95
Danger & *Family-Z*	18	.50				
Fixed Effects (shape-parameters)		.10				
Intercept			1.88	.18	10.66	
Points			.25***	.04	6.51	
Flux			.17***	.04	4.43	
Points:Flux			.11**	.04	2.93	
Random Effects		.40				
Participants						.73
Residual						.83

Beauty & *Family-Y*	20	.61				
Fixed Effects (shape-parameters)		.23				
Intercept			6.54	.29	22.44	
Points			.41***	.10	4.30	
Flux			.34**	.10	3.28	
Radius			.45***	.10	4.90	
Length			.00	.10	.05	
Points:Flux			-.01	.10	-.08	
Points:Radius			-.14	.14	-1.03	
Flux:Radius			-.49***	.13	-3.90	
Points:Length			.46***	.12	3.71	
Flux:Length			-.73***	.16	-4.52	
Radius:Length			.45***	.11	4.22	
Points:Flux:Radius			- .45**	.15	-2.95	
Points:Flux:Length			.10	.16	.63	
Points:Radius:Length			.94***	.19	5.00	
Flux:Radius:Length			.05	.14	.37	
Points:Flux:Radius:Length			-.27	.18	-1.49	
Random Effects		.38				
Participants						1.24
Residual						1.24
Beauty & *Family-Z*	20	.68				
Fixed Effects (shape-parameters)		.09				
Intercept			3.39	.36	9.33	
Points			-.43***	.05	8.42	
Flux			-.34***	.05	6.42	
Points:Flux			-.04	.05	.73	
Random Effects		.59				
Participants						1.61
Residual						1.17

Notes. R^2 calculated using the method by Nakagawa & Schielzeth (2013). *b* = Raw regression coefficients coefficient. *SE* = Standard Error for *b*. ':' denotes an interaction effect. Analysis using R packages: lme4 (1.1-12), lmerTest (2.0-32), & MuMIn (1.15.6). ***$p < .001$, **$p < .01$, *$p < .05$

Future efforts aiming to understand shape effects may seek to extrapolate the shape-parameters presented here. For such endeavors, we provide a few suggestions. First, the shape-parameters tested here should be examined within the context of its algorithm. For example, in **Table A8** we can see points flipping between a positive and negative β value across conditions. Also, the labels we use to describe each shape-parameter have been symbolically assigned and could therefore be interpreted and recreated in a way which results in dissimilarities. For example: *family-y's radius* could be described as the radius of distally extruding volumes, rather than the radius of the entire object. Second, not all shape-parameters may be equally discriminable (Folstein, Gauthier, & Palmeri, 2012). Not knowing the discriminability of each shape-parameter complicates generalizations of their power across different algorithms. Finally, multicollinearity was present amongst our randomly generated values. This further complicates the inferences that can be made regarding the relative contribution of individual shape-parameters. For example: the *length* shape-parameter is significant when the *flux* shape-parameter is not included in *family-y's* models. Therefore, as an example, it would be premature to claim that more extreme *flux* for *any* object would lead to heightened impressions of dangerousness. To investigate specific metrics, we suggest that future research document the discriminability of each shape-parameter and samples values for them non-randomly.

Appendix C

Could the effect shapes have on impressions be explained by other perceptual variables? Prior research has examined many specific hypotheses regarding how properties of visual stimuli relate to preferences, such as familiarity (e.g., Reber et al., 2004; Zajonc, 1980), an image's spatial frequency amplitude spectrum slope (e.g., Graham, Friedenberg, McCandless, & Rockmore, 2010; Graham & Redies, 2010). fractal dimension (e.g., Aks & Sprott, 1996; Spehar, Clifford, Newell, & Taylor, 2003), complexity (e.g., Phillips et al., 2010; Shortess, Clarke, Richter, & Seay, 2000), size (e.g., Chen, Tanaka, Matsuyoshi, & Watanabe, 2016; Konkle & Oliva, 2011), and curvature (e.g., Bar & Neta, 2006; Bertamini et al., 2016; Vartanian et al., 2013). Our stimuli, however, were designed to assess the reliability of shape's effects in general. Therefore, *a priori* the shape-parameters we used were not normalized according to previously explored perceptual variables (i.e., how objects belonging to *family-x* could map to metrics of curviness is not readily apparent). Nevertheless, it is still possible to measure the stimuli in terms of these perceptual variables. Thus, here we share the results of testing alternative perceptual variables to see if they already explain shapes effect on impressions of novel objects. The same 90 novel objects from study-2 were measured in terms of seven perceptual variables: subjective familiarity ('familiarity'), spatial frequency amplitude spectrum slope ('amplitude spectrum slope'), fractal dimension ('fractility'), image complexity ('complexity'), surface area ('area'), object volume ('volume'), and surface curvature ('curvature'). The stimuli consist of 30 objects generated from three shape-families (*family-x, family-y,* & *family-z*). Three of the perceptual variables measure the 3D object (volume, area, curvature), while the other four perceptual variables measure the 2D images (i.e., "new renderings").

Shape-parameters' correlation to other variables

Each of the three shape-families (*family-x, family-y, family-z*) were measured in terms of seven variables: familiarity, amplitude, fractility, complexity, area, volume, and curvature. Each of these perceptual variables were correlated with the shape-parameters, but there was no apparent regularity. The Pearson's *r* correlation between each variable and shape-parameter are shown in **A9**. Although differences between each object were dependent upon changes in the value of a shape-parameter, none of the perceptual variables were perfectly correlated with the shape-parameters. Thus, none of these perceptual variables alone explains the specific effects of shapes on shared impressions.

A9. Relating shape-parameters with other visual statistics.
Pearson's *r* correlation between shape-parameters with 2D image statistics and 3D object statistics.

	Familiarity	Amplitude	Fractility	Complexity	Area	Volume	Curvature		
							Gaussian Max	Gaussian Min	Mean Max
Family-X									
Points	.48*	.55**	-.32	.67***	.23	.14	.39*	-.32	.48**
Flux	.91***	.73***	-.91***	.82***	-.76***	-.86**	.50**	.16	.52**
Family-Y									
Points	.72***	.53**	.20	.83***	.17	.27	-.16	*NA*	-.13
Flux	.16	-.07	-.09	.10	-.29	-.26	-.07	*NA*	.19
Radius	.02	-.28	.48**	.11	-.46*	-.18	.30	*NA*	-.57**
Length	-.36*	-.23	-.41*	-.37*	-.26	-.64***	.07	*NA*	.46*
Family-Z									
Points	-.31	.52**	.34	.86***	.74***	.77***	-.06	-.28	-.07
Flux	-.59***	.09	.26	.51**	.69***	.30	-.23	.26	-.24

Notes. The image sizes were recorded in bytes. The original renders were 1000x1000 pixels. *NA*: all objects from family-y had a Gaussian-min value of 0 and therefore correlations could not be calculated. *$p<.05$ **$p<.01$ ***$p<.001$

Comparing models predicting impressions

The inference goal for comparing models of impressions is to determine if the models of impressions using a perceptual variable informed by prior research supersedes the model of impressions using shape-parameters in goodness of fit. Each model was a mixed effects linear regression with participants set as a random effect and a perceptual variable (or the shape-parameters) set as the fixed effects. We compare the goodness of each model's fit using a second-order Akaike Information Criterion (AIC_c) (Burnham & Anderson, 2004). The perceptual variables were analyzed as discrete models because of multicollinearity. As shown in **A9**, many of the variables and shape-parameters are indeed highly correlated—an unsurprising fact given that the perceptual variables are the consequent of having manipulated the shape-parameters. We hypothesized that the models of impressions using shapes would consistently feature the lowest AIC_c scores to show that the effects of shapes cannot be readily explained by previously explored perceptual variables. In addition to the AIC_c scores, we also report the proportion of variance, R^2, explained by the fixed effects within each model.

A10. Comparing the model of impressions based on shapes to other models.
Several variables related to prior vision research are compared with shapes in predicting impressions. Each variable is entered into its own model and the models are ranked by goodness of fit (lowest AIC_c score). Variance explained by the fixed effects (R^2_{fixed}) and total model (R^2_{total}) are also included.

Variable AIC_c R^2_{fixed} R^2_{total}	Danger			Beauty		
	Family-X	Family-Y	Family-Z	Family-X	Family-Y	Family-Z
1	Shape 1705.99 .53 .80	Shape 1573.85 .15 .61	Area 1390.23 .10 .50	Fractility 2269.83 .00 .36	Shape 2069.14 .23 .61	Area 1967.90 .09 .69
2	Familiarity 1723.09 .53 .79	Fractility 1550.21 .15 .60	Shape 1395.50 .10 .50	Complexity 2270.36 .00 .36	Fractility 2136.83 .16 .54	Shape 1983.85 .09 .68
3	Complexity 1804.47	Curvature 1573.10	Complexity 1406.16	Area 2270.50	Curvature 2166.87	Complexity 1990.69

	.49 .76	.13 .59	.09 .48	.00 .36	.14 .52	.08 .68
4	Fractility 1923.09 .43 .70	Volume 1680.13 .04 .49	Volume 1427.88 .07 .46	Volume 2270.67 .00 .36	Volume 2261.21 .06 .43	Volume 2007.33 .07 .67
5	Amplitude 2027.57 .37 .63	Area 1699.97 .02 .47	Familiarity 1465.54 .03 .42	Familiarity 2271.59 .00 .36	Complexity 2268.87 .05 .43	Familiarity 2081.08 .03 .62
6	Volume 2176.60 .25 .51	Complexity 1711.15 .01 .46	Amplitude 1469.62 .02 .42	Amplitude 2271.67 .00 .36	Familiarity 2278.55 .04 .42	Amplitude 2093.31 .02 .62
7	Curvature 2239.80 .19 .45	Familiarity 1714.17 .01 .46	Curvature 1471.54 .03 .42	Curvature 2273.51 .00 .36	Amplitude 2306.86 .01 .39	Fractility 2098.30 .02 .62
8	Area 2275.01 .15 .41	Amplitude 1721.60 .01 .45	Fractility 1480.86 .01 .40	Shape 2273.73 .00 .36	Area 2309.94 .01 .38	Curvature 2102.10 .02 .61

Notes. Impression data (from study-2; danger, N = 18; beauty, N = 20). Beauty of *Family-x* yielded no consensus so modeling the group results in 0 variance explained by fixed effects. Yet, they are still included in gray for continuity. Models were analyzed using *R* package *lme4* (version 1.12-12) and *AICc* scores were calculated using the *R* package *MuMIm* (version 1.15.6). Each variable was entered in the following manner: lmer(impressions ~ variable + (1 I participant). 'Impressions' is the average impression across each participant's two evaluations. 'Variable' is the variable being examined, such as shapes. All variables were scaled and centered per family. 'Participant' is the identification of each person, entered as a random effect.

Models with the best goodness of fit were those which employed shapes or 'area,' see **A10**. Models using shapes had the lowest AIC_c scores in three conditions: danger of *family-x*, danger of *family-y*, and beauty of *family-y*. The models using 'area' had the lowest AIC_c score in two conditions: danger of *family-z* and beauty of *family-z*.

The most consistently best fitting model were those using shapes. Shapes as fixed effects also always explained the most variance, R^2_{fixed}. Thus, understanding the shared impressions of novel objects can be uniquely researched by exploring specific shape-parameters. This is not to say that other perceptual variables such as familiarity, spatial frequency, fractility, complexity, size, or curviness do not contribute to the formation of an impression, but rather that there are more ways to understand the relationship between shapes and impressions than previously understood. These results support the notion that shapes map to more than just preferences. This is congruent with prior research, which explored impressions of "innovativeness" amongst car interiors (Leder & Carbon, 2005), or the "sacredness" and "dominance" found amongst certain geometrical figures (Costa & Bonetti, 2016); how shapes map to all impressions of all novel objects could be further elucidated using our approach.

More Information Regarding the Perceptual Variables:

Subjective Familiarity

Preferences amongst abstract stimuli are related to their subjective familiarity (Matlin, 1971; Zajonc, 1980), and could work by altering the cognitive and perceptual fluency of an object (Reber et al., 2004). Subjective familiarity ratings of each object were collected online using mTurk. 30 participants were recruited, however, 17 participants failed the embedded attention-check and also, provided data without consistency. Thus, the meaningfulness of measuring the subjective familiarity of procedurally generated novel objects should be interpreted with caution. Nevertheless, we proceeded with the analysis by incorporating the remaining data from 13 participants. The procedure was similar to study-2. Each object was presented to participants with the question "How familiar does this object seem to you?" and a scale ranging from 1 (not at all familiar) through 9 (extremely familiar); the object remained visible until the participant responded by keying a number. Each object was selected randomly from a shape-family. The presented order of each shape-family was randomized across participants. After the shape-families were presented once, a break was given before the shape-families were re-evaluated a second time.

Data from the 13 participants who passed the attention check were reliable. We assessed reliability by way of impression-consistency and impression-consensus (the method of: leave-one-out correlation with the mean); see study-1's methods for more detail. Significant tests were calculated using Fisher's r to z transformations and then compared against zero using planned t-tests. The level of impression-consistency was found to be significant for each shape-family; *family-x*, $r_M = .62$, $t(12) = 7.71$, $p < .001$, $d = 2.14$; *family-y*, $r_M = .55$, $t(12) = 5.42$, $p < .001$, $d = 1.50$; *family-z*, $r_M = .38$, $t(12) = 3.17$, $p = .008$, $d = .88$. The level of impression-consensus was also found to be significant for each shape-family—albeit weakly for *family-z*; *family-x*, $r_M = .68$, $t(12) = 7.11$, $p <$

.001, d = 1.97; *family-y,* r_M = .46, $t(12) = 5.03$, $p < .001$, d = 1.40; *family-z*, r_M = .16, $t(12)$ = 2.19, p = .049, d = .61. Thus, the average subjective familiarity scores for each object reflects the individuals who passed the attention check relatively reliably. These subjective familiarity scores were used to predict impressions.

Amplitude Spectrum Slope

Fourier spatial frequency amplitude spectrum slopes relate to the sharpness and edges within an image. Images of natural scenes have an average slope of -2.0, while images of objects regularly depict a higher average slope around -2.8 (Redies, Hasenstein, & Denzler, 2008). Natural scenes on average are preferred over images of abstract objects (Vessel & Rubin, 2010). The underlying theoretical basis of these prior observations are separate, the former about vision and the latter about semantics. Nevertheless, the observations are related and therefore we explored the implications of a possible relationship between impression and the amplitude spectrum slope of images of novel object. Specifically, we explored whether the images' amplitude spectrum slope explains how shapes relate to impressions.

The spatial frequency amplitude spectrum slope is calculated by fitting a straight line to a portion of the relationship between the log of the rotationally averaged amplitude spectrum and the log of the spatial frequency (i.e., cycles per image); specifically the portion between 10 and 256 cycles per image—a standard computation procedure for avoiding the effects of image artifacts (Redies et al., 2007, 2008). The value of the average amplitude spectrum slope for each shape-family in study-2 was congruent with prior research examining objects (Redies et al., 2008); *family-x, M* = -2.7; *family-y M* = -2.5; *family-z, M* = -2.8.

Fractal Dimension

Jackson Pollock's paintings often range in fractal dimensions between 1.1 and 1.9—the same range in which natural scenes are found to also possess (Spehar et al., 2003). It is possible that each image's fractal dimension meaningfully relates to people's impressions. Therefore, we explored whether the fractal dimension of an image explains how shapes relate to impressions.

We used ImageJ, image processing software, to calculate the fractal dimension of each image (Schneider, Rasband, & Eliceiri, 2012). To do so, the images were first converted into binary images using the default automatic threshold method. Then each fractal dimension was calculated using the fractal box count analysis with exponential box sizes: 2, 3, 4, 6, 8, 12, 16, 32, 64.

Image Complexity

In general, people tend to prefer simpler shapes over complex ones (Chen et al., 2016), yet the exact relationship between complexity and preferences is the subject of a long debate (e.g., Reber et al., 2004; Sherman, Grabowecky, & Suzuki, 2015). Nevertheless, we explored whether an image's objective complexity explains the relationship between shapes and impressions.

One objective measure of an image's complexity is its compressed file size; a measure that is correlated with subjective measures of complexity (Donderi, 2006). But unlike subjective complexity ratings, objective complexity ratings are immutable to any objective familiarity (i.e., prior exposure) with a shape (Forsythe, Mulhern, & Sawey, 2008). We measured the file size, in bytes, of our images in the jpeg file format.

Object Volume & Surface Area

Infants as young as 4.5 months old demonstrate the use of an object's size, along with shape, to individuate them (Wilcox, 1999). This basic ability to distinguish size is tied to preferences; people tend to prefer larger shapes, for example (Chen et al., 2016; Silvera, Josephs, & Giesler, 2002). People also have in mind a canonical visual size of an object and prefer 2D representations that are congruently sized (Konkle & Oliva, 2011). We explored the possibility that the size of objects relates to peoples' impressions and could therefore explain shapes' effects.

Using the Rhino software, we measured the volume and surface area of each object. Because the objects we test have never occupied physical space, the measurements are unitless. These measurements are proportional to the size of an object as it appears in a 2D image because the rendering process was uniform across all the objects.

Surface Curvature

People may have a perceptual bias for curvilinear shapes that becomes heightened when primed with a threatening word or fear-inducing video (LoBue, 2014). Smooth curves are also approached more quickly (Palumbo, Ruta, & Bertamini, 2015), and are preferred in architectural spaces (Vartanian et al., 2013). We explore whether the surface curvature of each object explains how shapes relate to impressions of novel objects.

Amongst the current literature on curvature's psychological effects, there have been many types of measurements (Gómez-Puerto, Munar, & Nadal, 2016). However, because prior approaches focused on 2D images and relatively simple contours, we therefore introduce a new type of measurement appropriate for 3D objects. Specifically, we recorded three variables which summarize the curvature of a 3D surface: Gaussian-max-curvature, Gaussian-min-curvature, and mean-max-curvature. These variables can be recorded using the curvature analysis tool in the Rhino software. The maximum and minimum Gaussian curvature depicts the magnitude of the most extreme synclastic (i.e., bowl-like or dome-like) and anticlastic (i.e., saddle-like) surfaces of an object. Positive values are synclastic, negative values are anticlastic, zero-values represent a flat surface. The maximum mean curvature depicts the most extreme concave/convex surface transition. There are multiple algorithms for estimating the Gaussian and mean curvature (Magid, Soldea, & Rivlin, 2007). The algorithm underlying the curvature analysis tool we use in Rhino can be found in chapter 3 of Giovanzana's thesis (2011).

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