Individual differences in visual salience vary along semantic dimensions

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What determines where we look? Theories of attentional guidance hold that image features and task demands govern fixation behaviour, while differences between observers are interpreted as 'noise'. Here, we investigated the fixations of > 100 human adults freely viewing a large set of complex scenes. We found systematic individual differences in fixation frequencies along six semantic stimulus dimensions. These differences were large (> twofold) and highly stable across images and time. Surprisingly, they also held for *first* fixations directed towards each image, which are thought to reflect 'bottom-up' visual salience. The dimensions of individual salience and their covariance pattern replicated across samples from three different countries, suggesting they reflect a fundamental biological space of attention. Our findings show that individual observers have stable salience biases, which can be captured along a canonical set of semantic dimensions. Salience reflects features of the observer as well as the image.

Introduction

Humans constantly move their eyes[1]. The foveated nature of the human visual system balances detailed representations with a large field of view. On the retina[2] and in visual cortex[3], resources are heavily concentrated towards the central visual field, resulting in the inability to resolve peripheral clutter[4] and the need to fixate visual objects of interest. Where we move our eyes determines which objects and details we make out in a scene[5,6].

Models of attentional guidance aim to predict which parts of an image will attract fixations based on image features[7–10] and task demands[11,12]. Classic salience models compute image discontinuities of low level attributes, such as luminance, colour and orientation[13]. These

low-level models are inspired by 'early' visual neurons and their output correlates with neural responses in subcortical[14] and cortical[15] areas thought to represent neural 'salience maps'. However, while these models work relatively well for impoverished stimuli, human gaze behaviour towards richer scenes can be predicted at least as well by the locations of objects[16] and perceived meaning[9]. When sematic object properties are taken into account, their weight for gaze prediction far exceeds that of low-level attributes[8,17]. A common thread of low- and high-level salience models is that they interpret salience as a property of the image and treat inter-individual differences as unpredictable[7,18], often using them as a 'noise ceiling' for model evaluations[18].

However, even the earliest studies of fixation behaviour noted considerable individual differences[19,20], and basic occulomotor traits vary reliably between observers[21–26]. Recent twin-studies revealed that social attention and gaze traces across complex scenes are highly heritable[27,28]. This suggests individual differences in fixation behaviour are not random, but systematic. However, it is largely unclear, *how* individuals differ in their fixation behaviour and what may explain these differences. Can individual fixation behaviour be captured along a limited set of dimensions?

Here, we tested the hypothesis that individual gaze reflects *salience biases* along a limited number of semantic dimensions. We investigated the fixation behaviour of > 100 human adults freely viewing 700 complex scenes, containing thousands of semantically annotated objects[8]. We quantified salience biases as the *individual* proportion of cumulative fixation time or *first* fixations landing on objects with a given semantic attribute. *First* fixations are thought to reflect 'automatic' or 'bottom-up' salience[29] and therefore may reveal individual differences with a deep biological root and under little voluntary control. We tested the reliability of such biases across random subsets of images and re-tests after several weeks. To test the generalizability of

salience biases, we replicated their set and covariance pattern across independent samples from three different countries. Finally, we explored whether individual salience biases are related to personality and perception, focussing on the example of face salience and face recognition skills for the latter.

Results

Reliable Salience Biases

We tracked the gaze of healthy human adults freely viewing a broad range of images depicting complex everyday scenes[8]. A first sample was tested at University College London, UK (*Lon*; *n* = 51), and a replication sample at University of Giessen, Germany (*Gi_1*; n = 51). The replication sample was also invited for a re-test after two weeks (*Gi_2*; *n* = 48). Additionally we re-analysed a public dataset from Singapore (*Xu et al.* [8]; *n* = 15).

First, we probed the individual tendency to fixate objects with a given semantic attribute, measuring duration-weighted fixations across a free-viewing period of 3s. We considered a total of twelve semantic properties, which have previously been shown to carry more weight for predicting gaze behaviour (on an aggregate group level) than geometric or pixel-level attributes[8]. To test the consistency of individual salience biases across independent sets of images, we probed their reliability across 1000 random (half-)splits of 700 images. We found consistent individual salience biases ($r > .6$) for six of the 12 semantic attributes: Neutral *Faces*, *Emotion*al Faces, *Text*, objects being *Touched*, objects with a characteristic *Taste* (i.e. food and beverages) and objects with implied *Motion* (Figure 1, grey scatter plots).

Observers showed up to two-fold differences in the cumulative fixation time attracted by a given semantic attribute and the median consistency of individual differences across image splits for these six dimensions ranged from $r = .64$ $P < .001$ (*Motion*) to r = .94, $P < .001$ (*Faces*; Table 1, left hand side; *P*-Values Bonferroni corrected for 12 consistency correlations).

Previous studies have argued that extended viewing behaviour is governed by cognitive factors, while early or first fixations towards an image are governed by 'bottom-up' salience[29]. Others however, have found that perceived meaning[9] and semantic stimulus properties[8] are important predictors of gaze behaviour from the first fixation. We found consistent individual differences also in the proportion of *first* fixations directed towards each attribute. The range of individual differences in the proportion of *first* fixations directed to each of the six attributes was even larger than that for all fixations (up to threefold). Importantly, these inter-observer differences were consistent for all dimensions found for cumulative fixation time except *Motion* ($r = .34$, *n.s.*), ranging from $r = .57$, $P < .001$ (*Taste*) to r = .88, $P < .001$ (*Faces*; Table 1, right hand side and green scatter plots in Figure 1; *P*-Values Bonferroni corrected for 12 consistency correlations).

These salience biases proved robust for different splits of images and replicated across datasets from three different countries (Figure 2a; Table 1). For the confirmatory *Gi_1* dataset we tested the same number of observers as in the original *Lon* set (> 95% power to detect consistencies of $r > .5$). For cumulative fixation time (grey histograms in Figure 2a), the six dimensions identified in the *Lon* sample (top row), closely replicated in the *Gi_1* and *Gi_2* samples (middle rows), as well as in a re-analysis of the public *Xu et al*. dataset (bottom row), with consistency correlations ranging from .65 (*Motion* in the *Gi_1* set) to .95 (*Faces* in the *Xu et al.* set; left column of Table 1). Similar was true for *first* fixations, although the consistency

correlation for *Emotion* missed statistical significance in the small *Xu et al.* dataset (green histograms in Figure 2a; right column of Table 1).

The individual salience biases we found were consistent across subsets of diverse, complex images. To test whether they reflected stable observer traits, we additionally tested their re-test reliability for the full image set across a period of 6-43 days (average 16 days; the *Gi_1* and *Gi_2* datasets). Salience biases along all six semantic dimensions were highly consistent over time (Figure 2b). This was true for both, cumulative fixation time (re-test reliabilities ranging from $r = .68$, $P < .001$ (*Motion*) to r = .85, $P < .001$ (*Faces*); left column of Table 1; grey bars in Figure 2b) and *first* fixations (re-test reliabilities ranging from $r = .62$, $P < .001$ (*Taste*) to r = .89, $P < .001$ (*Text*); right column of Table 1; green bars in Figure 2b).

Finally, we tested the relationship between individual salience and visual field biases. Different types of objects tend to appear at different parts of the visual field and recent findings suggest that observers are attuned to these contingencies[30–32]. The most prominent spatial bias in the scene stimuli we used was a strong tendency for faces to appear in the upper visual field (~75%). Individual face salience (% *first* fixations) was indeed correlated with a general upper visual field bias (as indexed by the median elevation of *first* fixations towards images not containing a face; $r = .49$-$.78$ across samples, all $P < .05$). Crucially, however, individual differences in face salience persisted independent of this spatial bias. Individual face salience in the *lower* and upper visual field were highly correlated with each other ($r = .61$-$.87$ across samples, all $P < .05$; see Supplementary Methods and Supplementary Fig. 1 for details).

Covariance Structure of Salience Biases

Having established reliable individual differences in fixation behaviour along semantic dimensions, we further explored the space of these biases by quantifying the covariance between them. For this analysis we collapsed neutral and emotional faces into a single *Faces* label, because they are semantically related and corresponding biases were strongly correlated with each other (r = .74, $P < .001$; $r = .81$, $P < .001$ for cumulative fixation times and first fixations, respectively). Note that we decided to keep these two dimensions separated for the analyses above because the residuals of fixation times for emotional faces still varied consistently when controlling for neutral faces (r = .73, $P < .001$), indicating an independent component (however the same was not true for *first* fixations, r = .24, *n.s.*).

The resulting five dimensions showed a pattern of pairwise correlations that allowed the identification of two clusters (Fig. 3b, left hand side). This was illustrated by the projection of the pairwise (dis-)similarities onto a two-dimensional space, using metric dimensional scaling (Fig. 3b, right hand side). *Faces* and *Motion* were positively correlated with each other, but negatively with the remaining three attributes *Text*, *Touched* and *Taste*. Interestingly, *Faces,* the most prominent dimension of individual fixation behaviour, was strongly anti-correlated with *Text* and *Touched*, the second and third most prominent dimensions (*Text*: r = -.62, $P < .001$ and r = -.47, $P < .001$ for cumulative fixation times and first fixations, respectively, Fig. 3a, left hand side; *Touched*: r = -.58, $P < .001$ and r = -.80, $P < .001$, Fig. 3a, right hand side). These findings closely replicated across all four datasets (Fig. 4). Pair-wise correlations between (z-converted) correlation matrices from different samples ranged from .68 to .95 for cumulative fixation times and from .91 to .98 for first fixations.

Correlates of Salience Biases

To explore potential correlates of individual salience biases, we first explored their relationship with personality variables. Observers in the *Lon* sample completed questionnaires for seven personality dimensions, including the Big Five[33], Sensation Seeking[34] and High Sensitivity[35] (see Methods for details). We tested all 7x6 pairwise correlations between personality traits and individual salience biases, applying family-wise error correction for multiple comparisons[36]. Results showed no significant relationship between personality variables and cumulative fixation times (all $r < .39$, *n.s.*; Fig. 5b, left hand side), or *first* fixations (all $r < .23$, *n.s.*; Fig. 5b, right hand side).

Next, we aimed to test the perceptual implications of individual salience biases. We focussed on the most prominent salience bias for *Faces*, as indexed by the individual proportion of *first* fixations landing on faces (which is thought to be an indicator of low-level or bottom-up salience[29]). 46 observers from the *Gi* sample took the Cambridge Face Memory Test (CFMT) and we tested the correlation between individual face salience and face recognition skills. CFMT scores and the individual proportion of *first* fixations landing on faces correlated with $r = .41$, $P < .005$. Interestingly, this correlation did not hold for the individual proportion of total cumulative fixation time landing on faces, which likely represents more voluntary biases in viewing behaviour ($r = .21$, *n.s.*; Fig. 5a).

Discussion

Individual differences in gaze traces have been documented since the earliest days of eyetracking[19,20]. However, salience models have routinely ignored them and the nature of these

differences was unclear. Our findings show that they can be captured by a canonical set of semantic salience biases. These salience biases were highly consistent across hundreds of complex scenes, proved reliable in a re-test after several weeks and persisted independently of correlated visual field biases. This shows that visual salience is not just a factor of the image; individual salience biases are a stable trait of the observer.

Interestingly, not only the set of these biases replicated across independent samples from three different countries, but also their covariance structure. This may partly be driven by environmental and image statistics (for instance, faces are more likely to move than food). But it probably also reflects a deep-rooted neurobiological basis of these biases. This possibility is underscored by earlier studies showing that the visual salience of social stimuli is reduced in individuals with autism spectrum disorder[27,38,39] and most importantly by recent twin studies, showing that individual differences in gaze traces are heritable[27,28]. The gaze trace dissimilarities investigated in these studies probably are a manifestation of the salience biases we found here. Therefore these salience biases likely have a strong genetic component. Future studies should test this hypothesis directly.

Recent findings in macaque show that face deprived monkeys have a drastically reduced fixation bias towards faces and an increased bias towards hands. These differences in fixation behaviour were accompanied by an underdevelopment of domain specific face patches in the temporal cortex and a relative overdevelopment of hand preferring patches[40]. In our study, fixation biases towards the *Touched* label imply strong attentional guidance by hands (see Fig. 1 for examples). It is tempting to speculate that the strong anti-correlation we found between fixation biases towards *Faces* and *Touched* reflects individual differences in developmental exposure and cortical layout. The same could apply to the anti-correlation between *Faces* and

Text, two stimulus classes which have previously been proposed to compete for cortical territory[41]. It is worth noting that most of the reliable dimensions of individual salience biases we found correspond to domain specific patches of the ventral path (as is true for *Faces*[42–44], *Text*[41,45], *Motion*[46], *Touched*[40,47,48] and maybe *Taste*[49]). Future studies should directly test the relationship between salience biases and the individual functional architecture of the ventral stream.

Finally, our findings raise important questions about the individual nature of visual perception. Two observers presented with the same image likely end up with a different percept[5,6] and interpretation[50] of this image when executing systematically different eye movements. Vision scientists may be chasing a phantom when 'averaging out' individual differences to study the 'typical observer'[51–53] and *vice versa* perception may be crucial to understand individual differences in cognitive abilities[54], personality[55,56], social behaviour[27,38] and development[39].

We only took a first step towards investigating the perceptual and social implications of salience biases here. Individual face salience was significantly correlated with face recognition skills. Interestingly, this was only true when considering the proportion of *first* fixations attracted by faces, which likely represents a 'bottom-up' bias under limited voluntary control. This raises questions about the ontological interplay between face salience and recognition. Small initial differences may grow through mutual reinforcement of face fixations and superior perceptual processing. Future studies should track the development of salience biases and their correlates longitudinally.

We found no significant correlations between salience biases and personality factors captured by standard psychometric questionnaires. Given the large number of tests and control for family-wise error, we cannot rule out the existence of small or medium effects. It is still interesting that salience biases are not strongly related to psychometric personality. The salience biases we found have unusually high magnitudes (up to factor 3) and reliability (up to and greater than .9) for objective psychological traits. They appear to document fundamental differences in visual attention and perception, which are main filters of incoming information about our surroundings. Future studies should explore how salience biases can inform and enrich the science of individual differences.

In summary, we found a small set of semantic dimensions that span a space of individual differences in fixation behaviour. These dimensions replicated across culturally diverse samples and also applied to the first fixations directed towards an image. Visual salience is not just a function of the image, but also a trait of the observer.

Methods

Subjects

The study comprised three original datasets (the *Lon*, *Gi_1* and *Gi_2* samples) and the re-analysis of a public dataset (the *Xu et al*. sample[8]).

54 healthy adults with normal or corrected-to normal vision participated in the experiment conducted at University College London, UK. The local institutional review board approved the study and participants provided written informed consent. Reimbursement was 25£. Eyetracking failed for three participants due to technical problems, leaving 51 in the *Lon* sample

(25 males, 4 left handed, mean age 23 with a standard deviation of 4 years). For two of these participants, data from one block was missing due to a recording failure; the remaining data from these participants were entered into the analysis nonetheless. Control-analysis showed that the results remained virtually unchanged when these data were excluded. 46 of the *Lon* participants additionally completed three personality questionnaires administered online: The IPIP-NEO 120 (NEO)[33] to measure the Big Five[57]; the Highly Sensitive Person Scale (HSP)[35] and the Brief Sensation Seeking Scale (BSSS)[34].

51 healthy adults with normal or corrected-to normal vision participated in the experiment conducted at Justus-Liebig Universität Giessen, Germany (the *Gi_1* sample; 11 males, 5 left handed, mean age 24, with a standard deviation of 4 years). For one of these participants, data from one block was missing due to a recording failure; the remaining data from this participants were entered into the analysis nonetheless. Control-analysis showed that results remained virtually unchanged when these data were excluded. The local institutional review board approved the study and participants provided written informed consent. Reimbursement was 30€ or course credits.

48 of the *Gi_1* participants returned to the lab for a re-test (the *Gi_2* sample). The period between tests was 16 days on average (minimum 6 days; maximum: 43 days; standard deviation: 7 days). 46 of the *Gi* participants additionally completed an online version of the Cambridge Face Memory Test (CFMT)[58].

The public *Xu et al*. dataset comprises 15 participants with a reported age range of 18-30 years[8].

Stimuli

Participants were presented with 700 natural images depicting a wide variety of complex everyday scenes (http://www-users.cs.umn.edu/~qzhao/predicting.html). Semantic metadata[8] consist of binary pixel maps for 5551 objects in these images and accompanying labels for 12 semantic dimensions. We modified the provided labels to minimize overlap between them in the following way: The (neutral) *Faces* label was removed from all objects with the *Emotion* label (i.e. emotional faces); The *Smell* label was removed from all objects with the *Taste* label; The *Operable* and *Gazed* labels were removed from all objects with the *Touched* label; The *Watchable* label was removed from all objects with the *Text* label. This step allowed to test individual differences in fixation attraction for a given dimension largely independently from the others. Without this step some of the attributes would have been perfectly confounded (for instance, all text is watchable; all emotional faces are faces).

In each experiment, participants viewed seven blocks of 100 images on a screen. Stimulus presentation and data collection was coded in MATLAB Version R2016b (MathWorks, Natick, MA) using Psychtoolbox Version 3.0.12[59,60]. For the *Lon* and *Gi_1* samples the order of images was fixed across all participants and each image was presented for 3s, with a self-paced period of a central fixation dot in between. Participants were simply instructed to 'look at the images in any way [they] want' and initiated the onset of each image with a press of the space bar. The re-test of the Giessen sample (*Gi_2*) followed the same procedure as the first appointment, with the exception of the order of images presented, which was shuffled relative to the first appointment (but again constant across participants).

Participants in the *Lon* sample sat at a distance of ~65 cm from a screen and saw the stimuli at a resolution of 800 x 600 pixels and a size of 19.2 x 14.4 degrees visual angle. Participants in the *Gi* samples sat with their head in a chinrest, at a distance of 46 cm from the screen and saw the stimuli at a resolution and size of 1000x750 pixels and a size of 37.2 x 27.9 degrees visual angle. The *Xu et al*. sample saw stimuli at a size of 33.7 x 25.3 degrees visual angle. Further details on this sample can be found in the original publication by Xu et al.[8].

Data Collection

The gaze of participants in the *Lon* sample was sampled remotely and binocularly with a Tobii EyeX (Tobii Technologies, Danderyd, Sweden) at a frequency of ~55 Hz[61]. Eyetracking data from the *Gi* samples was collected from the left eye with a tower mounted Eyelink 1000 (SR Research, Ottawa, Canada) at a frequency of 2 kHz (the *Xu et al*. data were collected with a remote Eyelink 1000[8]).

At the beginning of each block, participants completed a nine-point calibration and validation procedure, which was repeated if necessary. For the *Gi* samples, fixation data was collected online using the 'normal' setting of the Eyelink parser (saccade velocity and acceleration thresholds of 30 d.v.a./s and 9500 d.v.a./s^2, respectively) and the default drift check procedure in each inter-trial interval. Raw data from the *Lon* sample was converted to fixation data offline (see below).

Data Processing and Analyses

Raw eyetracking data from the *Lon* sample were transformed into fixation data applying a saccade threshold of 30 d.v.a./s and taking the median x and y position of fixation samples as the respective fixation location. Fixations were drift-corrected in a block-wise fashion, centering on the median of fixation locations registered at image onsets during the respective block.

Onset fixations and fixations with a duration below 100ms were disregarded for all datasets (minimum fixation duration following standard recommendations by SR Research and Xu *et al.* [8]). Fixations that fell on or within a distance of ~0.5 d.v.a from a labelled object were assigned the corresponding label. Unlabelled fixations were disregarded for the calculation of cumulative fixation times and the individual proportion of *first* fixations (see below).

In order to quantify the individual tendency to fixate objects bearing a given attribute label, we first calculated the cumulative fixation time for all labelled fixations made by a given observer to a given image set. This allowed us to calculate the proportion of this time spent on a given attribute in a second step.

The *first* fixations analysis considered the proportion of labelled *first* fixations (after image onset) landing on objects with a given attribute for a given observer and image set. Individual proportions of cumulative fixation time and first fixations were expressed in %.

Consistency and re-test correlations

To estimate the consistency of individual differences in % cumulative fixation time or % first fixations along a given attribute dimension, we calculated these measures independently for two random halves of the image for each observer and then correlated individual differences for

one half of the images with the other using Pearson correlation coefficients. This procedure was repeated 1000 times. We inspected the frequency histograms of all correlations (Fig. 2) and considered the median correlation coefficient across random image splits as an indicator of consistency. The accompanying two-sided *P*-values were Bonferroni adjusted for twelve comparisons in the *Lon* sample,

To estimate the re-test reliability of individual differences in % cumulative fixation time or % first fixations for a given attribute, we correlated the corresponding values for the first session of the *Gi* sample with those of the second.

Covariance patterns between dimensions and correlations with other measures

To investigate the covariance pattern between the dimensions of consistent individual differences in fixation behaviour, we inspected pair-wise Pearson correlation matrices (Fig. 3B and 4, left hand side). We further used metric multidimensional scaling to project the pair-wise dissimilarities between dimensions (defined as $(1-r)^2$) onto distances in a two-dimensional space (Fig. 3B and 4, right hand side). To further test the stability of covariance patterns between datasets we calculated pair-wise Pearson correlations between Fisher Z-transformed correlation matrices from different samples.

To explore the relationship between personality and individual gaze behaviour, we computed all pairwise correlations between reliable dimensions of salience biases and personality. Specifically we correlated individual salience biases for *Faces*, *Emotion*, *Text*, *Taste*, *Touched* and *Motion* with the Big Five as determined by the IPIP-NEO 120[33] *Neuroticism* (N),

Extraversion (E), *Openness* (O), *Assertiveness* (A), *Conscientiousness* (C), with high sensitivity (HS) as determined by the Highly Sensitive Person scale[35], and with sensation seeking (SS) as determined by the Brief Sensation Seeking Scale[34]. The resulting 6x7 correlation matrix was computed separately for the proportion of cumulative fixation time and for that of *first* fixations; accompanying *p*-values were adjusted for multiple testing using the Holm-Bonferroni correction for family-wise errors[36].

To test the perceptual implications of salience biases, we concentrated of the example of faces. Specifically, we probed a correlation between individual face salience as indicated by the proportion of cumulative dwell time or *first* fixations landing on faces and total scores in the Cambridge Face Memory Test[58]. This standard test of individual face recognition skills was administered online to participants from the *Gi* sample, after the first eyetracking session.

Availability of data and code

Anonymised fixation data and code to reproduce the results presented here are freely available at https://osf.io/n5v7t/

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Table

	Ind. % fixation time				Ind. % first fix			
	r	***P***	**range [%]**	**max/min**	***r***	***P***	**range [%]**	**max/min**
Faces - Lon	.94	<.001*	24-43	1.80	.88	<.001*	24-43	1.77
– Gi_1	.91	<.001	21-35	1.64	.88	<.001	15-42	2.82
– Gi_2	.91	<.001	17-34	1.99	.89	<.001	15-43	2.76
– Xu *et al.*	.95	<.001	23-35	1.50	.86	<.001	24-41	1.69
- Re-test (Gi_1-2)	.80	<.001	-	-	.86	<.001	-	-
Emotion - Lon	.82	<.001*	8-15	1.93	.69	<.001*	9-18	1.88
– Gi_1	.80	<.001	8-13	1.68	.76	<.001	8-17	2.20
– Gi_2	.82	<.001	7-13	1.79	.75	<.001	8-17	2.22
- Xu *et al.*	.89	<.001	8-12	1.56	.48	.07	13-17	1.31
- Re-test (Gi_1-2)	.85	<.001	-	-	.79	<.001	-	-
Text - Lon	.81	<.001*	9-16	1.76	.77	<.001*	6-17	2.96
– Gi_1	.90	<.001	9-19	1.97	.82	<.001	5-16	3.11
– Gi_2	.91	<.001	9-20	2.21	.82	<.001	4-17	3.91
- Xu *et al.*	.94	<.001	8-18	2.16	.83	<.001	4-13	3.25
- Re-test (Gi_1-2)	.84	<.001	-	-	.89	<.001	-	-
Touched - Lon	.73	<.001*	11-16	1.52	.73	<.001*	6-16	2.48

– Gi_1	.74	<.001	9-15	1.63	.71	<.001	6-15	2.65
– Gi_2	.75	<.001	9-16	1.67	.72	<.001	6-16	2.74
- Xu *et al.*	.91	<.001	9-16	1.85	.65	.008	7-13	1.81
- Re-test (Gi_1-2)	.70	<.001	-	-	.78	<.001	-	-
Taste - Lon	.70	<.001*	10-16	1.58	.57	<.001*	10-16	1.67
– Gi_1	.70	<.001	11-15	1.38	.29	.04	10-14	1.36
– Gi_2	.74	<.001	10-17	1.67	.50	<.001	9-16	1.75
- Xu *et al.*	.84	<.001	11-16	1.44	.69	.004	9-15	1.72
- Re-test (Gi_1-2)	.78	<.001	-	-	.62	<.001	-	-
Motion - Lon	.64	<.001*	28-36	1.31	.35	.15*	31-39	1.25
– Gi_1	.65	<.001	28-34	1.22	.52	<.001	30-38	1.29
– Gi_2	.73	<.001	26-33	1.29	.52	<.001	28-37	1.32
- Xu *et al.*	.85	<.001	28-33	1.19	.62	.01	33-40	1.22
- Re-test (Gi_1-2)	.68	<.001	-	-	.78	<.001	-	-

Table 1. Range and median consistency of individual differences in fixation behaviour towards six semantic dimensions. The left hand side of the table shows data for individual differences in the proportion of cumulative fixation time (across three seconds) spent on objects with the respective semantic attributes. The right hand side shows data on individual differences in the proportion of first fixations after image onset landing on objects with those attributes. For

each semantic attribute, the data from different samples (*Lon*, *Gi_1, Gi_2* and *Xu et al*.) is presented in separate rows. The range across participants is given in % fixation time or % of first fixations and the max/min ratio indicates the relative difference between observers attracted the most or least by a given attribute. Pearson correlations (*r*) indicate the median split-half correlation of individual differences across 1000 random image splits and the corresponding *P*-value (Bonferroni corrected for 12 semantic attributes in the *Lon* sample, as indicated by the *). Consistency correlations failing to reach statistical significance are highlighted in red. The final row for each attribute shows the corresponding re-test reliability across several weeks.

Figures

Figure 1. Consistent individual differences in fixation behaviour along six semantic dimensions. For each semantic attribute, the grey scatter plot shows individual proportions of cumulative fixation time for the odd *versus* even images in the *Lon* dataset. The green scatter plot shows the corresponding individual proportions of *first* fixations after image onset. For each dimension, two example images are given and overlaid with the fixations from one observer strongly attracted by the corresponding attribute (orange frames) and one observer weakly

attracted by it (blue frames). The overlays show the first fixation after image onset as a green circle; any subsequent fixations are shown in purple. The two data points corresponding to the example observers are highlighted in the scatter plot, corresponding to the colour of the respective image frames.

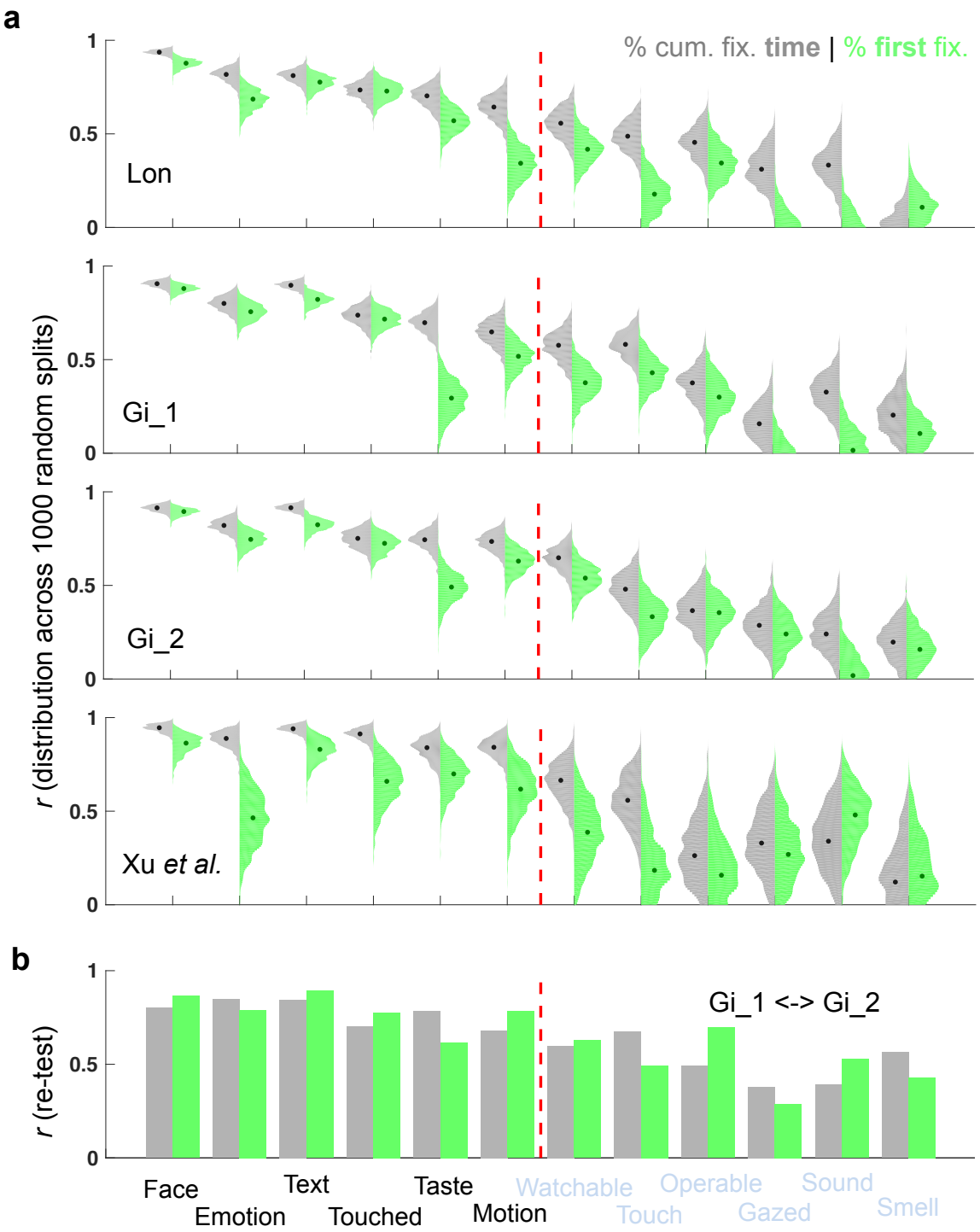


Figure 2. Consistency of results across images, datasets and time. (a) Distribution plots of consistency correlations for each of the twelve semantic dimensions tested (as indicated by the labels on the x-axis in b). Results are shown separately for the four observer samples tested (as

indicated by the row labels). Gi_1 and Gi_2 refer to the first and second appointment of the Gi sample. The grey left-hand leaf of each distribution plot shows a histogram of split-half correlations for 1000 random splits of the image set, the green right hand leaf shows the corresponding histogram for *first* fixations after image onset. Overlaid dots indicate the median consistency correlation for each distribution. High split-half correlations indicate consistent individual differences in fixation behaviour across images for a given dimension. The dashed red line separates the six attributes found to be consistent dimensions of individual differences in the *Lon* sample from the remaining dimensions. (**b**) Re-test reliability across Gi_1 and Gi_2. The magnitude of re-test correlations for individual dwell time and proportion of first fixations is indicated by grey and green bars, respectively. All correlation and *P*-values can be found in Table 1.

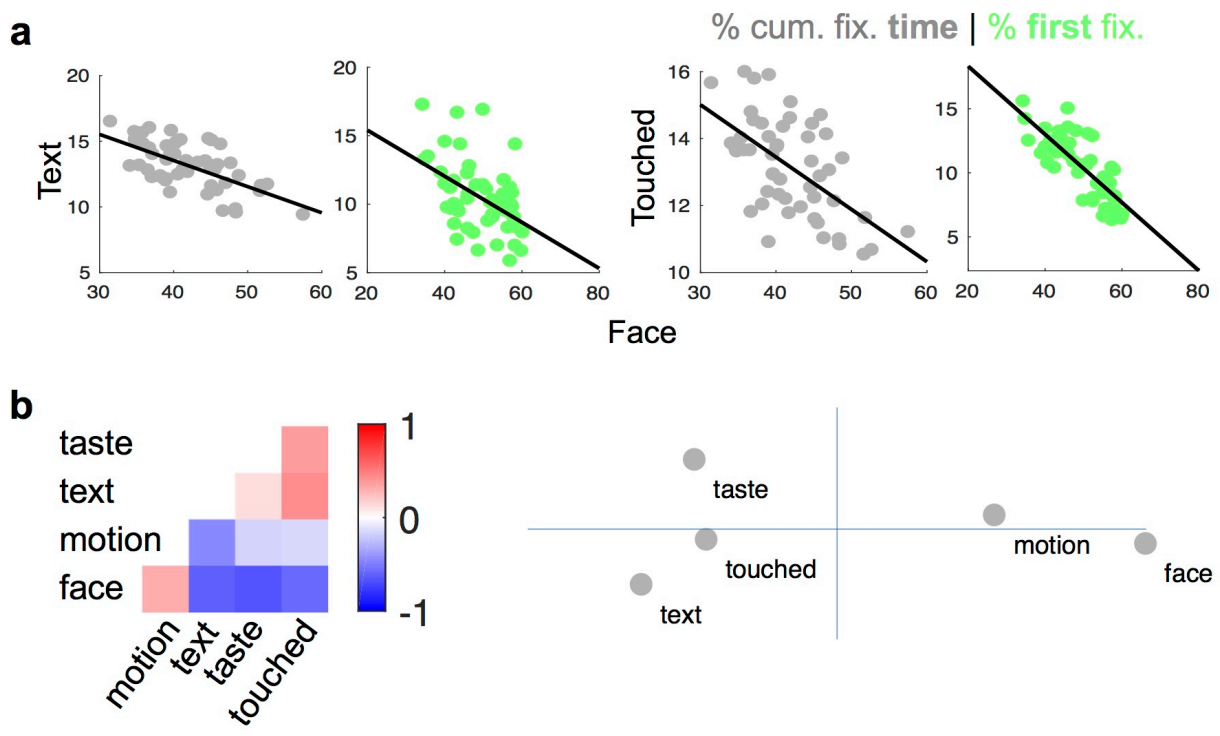


Figure 3. Covariance of individual differences along semantic dimensions. (**a**) Grey scatter plots show the individual proportion of cumulative fixation time (in %) for *Faces versus Text* (left hand side) and *Faces versus* objects being *Touched* (right hand side). Green scatter plots show the corresponding data for the individual proportion of *first* fixations after image onset. (**b**) Correlation matrix for individual differences along five semantic dimensions (left hand side; note that the labels for emotional and neutral faces were collapsed for this analysis). Colour indicates pairwise Pearson correlation coefficients as indicated by the bar. *Motion* and *Face* are positively correlated with each other, but negatively correlated with the remaining dimensions, as captured by a two-cluster solution of metric dimensional scaling to two dimensions (right hand side). All data shown are based on individual proportions of fixation time in the *Lon* dataset. The corresponding supplemental Figure S1, shows the consistency of this pattern for the proportion of first fixations and across all four datasets.

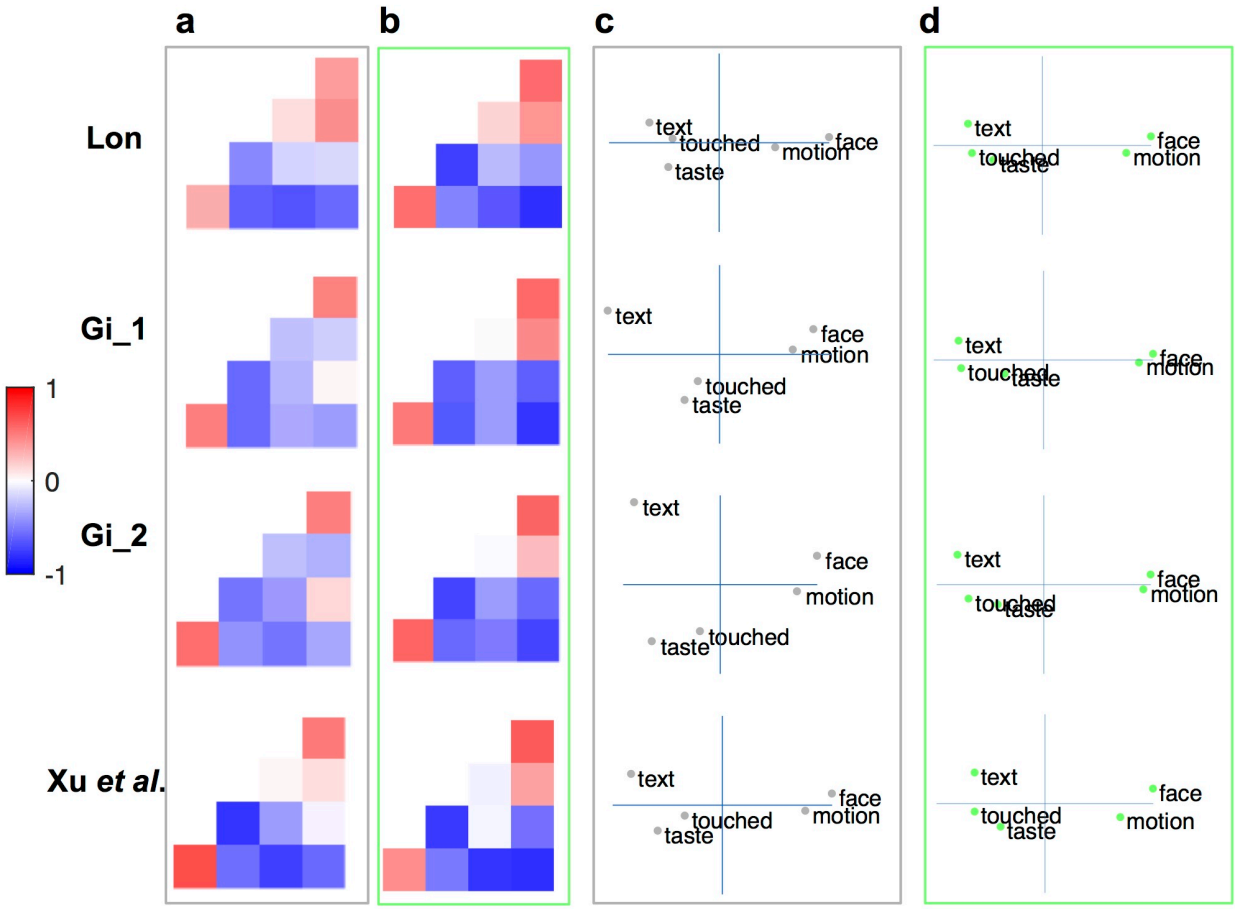


Figure 4. Consistency of covariance pattern across datasets. (**a**) shows covariance patterns for dimensions of individual differences in cumulative fixation durations and (**b**) those for individual differences in the proportion of *first* fixations. Each row shows the results for one dataset as indicated (Lon, Gi_1, Gi_2 and Xu *et al*.). Colours of the left hand correlation matrices indicate pairwise Pearson correlation coefficients between dimensions as indicated by the bar. Please refer to Figure 3 for dimension labels (from top to bottom: taste, text, motion, face; from left to right: motion, text, taste, touched). Note the similarity of covariance patterns between datasets. All pairwise correlations between (Fisher z-transformed) correlation matrices were >.68 for cumulative fixation durations and >.90 for first fixations. The right hand side scatter plots show the results of metric multidimensional scaling onto two dimensions for cumulative fixation

duration (**c**) and first fixations (**d**). This analysis yielded a distinct cluster for *Faces* and *Motion*, as well as a cluster for *Text*, *Touched Taste* for first fixations in all datasets. This structure was very similar for cumulative dwell time, with the exception of *Text* separating from *Touched* and *Taste* in the Gi_1 and Gi_2 data.

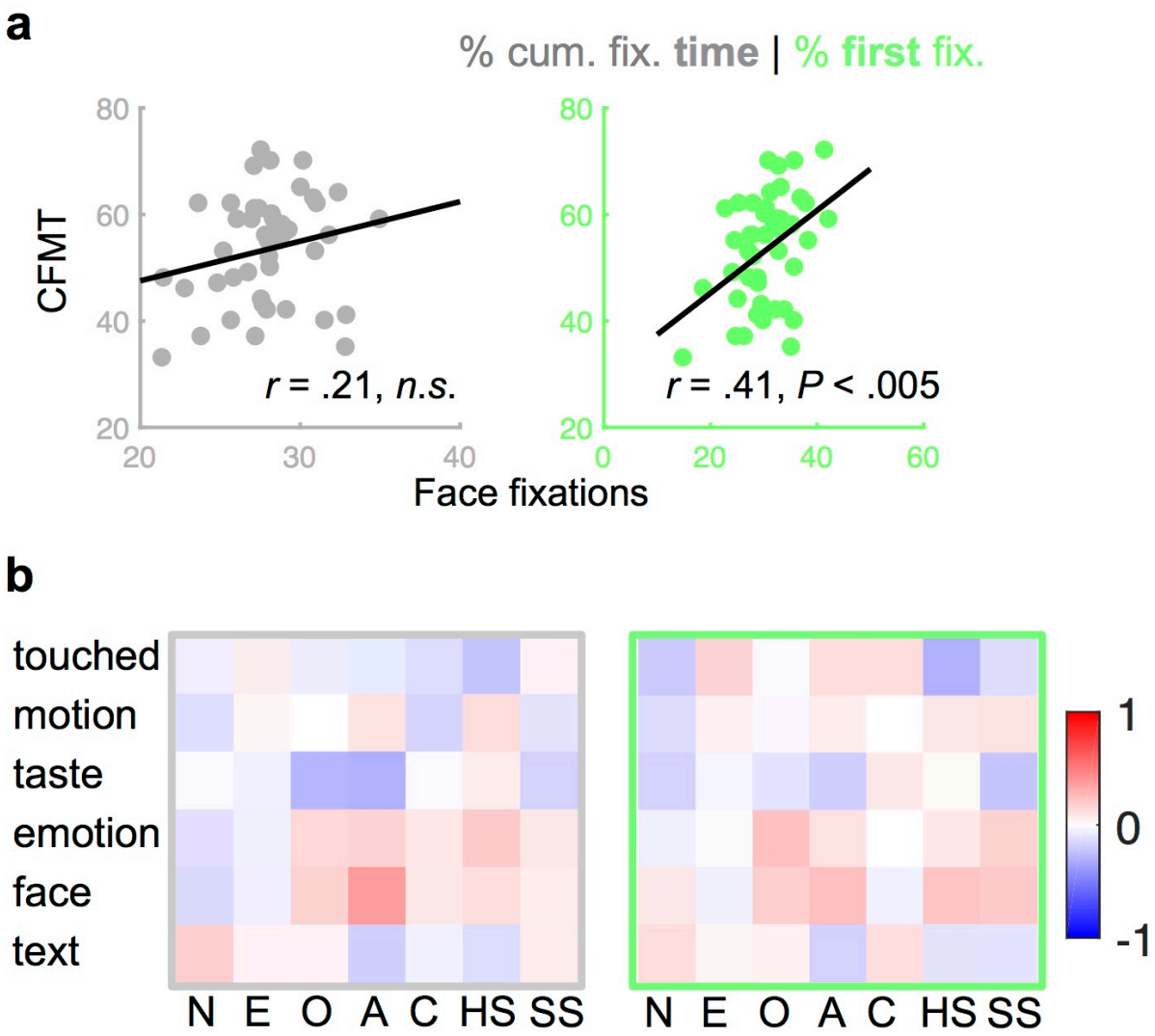


Figure 5. Correlations between fixation behaviour, face recognition skills and personality. (**a**) Performance on the Cambridge Face Memory Test (CFMT) correlated significantly with the individual proportion of first fixations landing on faces when freely viewing complex scenes (green, right hand side). This correlation was not significant for cumulative fixation time across the viewing time of three seconds (grey, left hand side). (**b**) Neither cumulative fixation time (grey frame, left hand side), nor the proportion of first fixations (green frame, right hand side) towards any of the six dimensions of individual gaze behaviour correlated significantly with any

of the tested dimensions of personality (N: Neuroticism, E: Extraversion, O: Openness, A: Assertiveness, C: Conscientiousness, HS: High Sensitivity, SS: Sensation Seeking). All data from the Gi_1 sample.

Supplementary Information

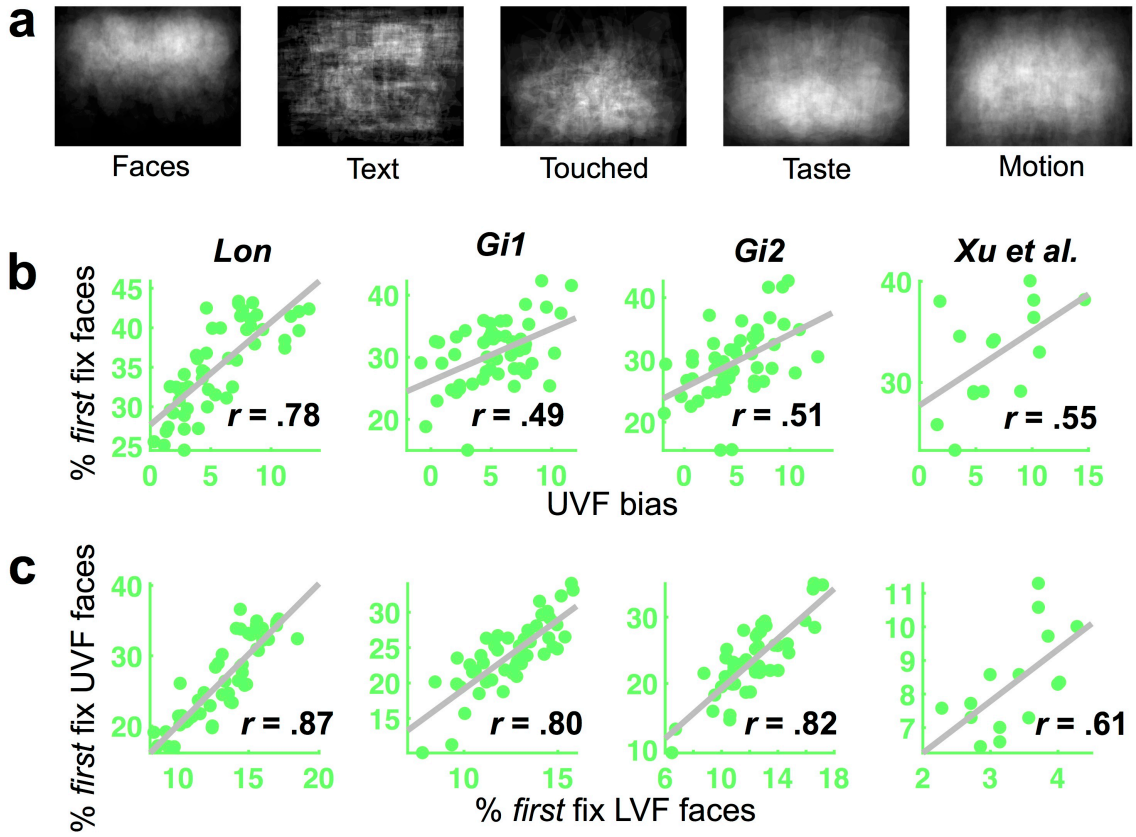
Supplementary Methods

To test the relationship between individual salience and visual field biases, we first explored the distribution of objects corresponding to dimensions of individual salience across image space (Supplementary Fig. 1a; neutral and emotional faces collapsed into *Faces*). The most prominent spatial bias in the scene stimuli was a strong tendency for faces to appear in the upper visual field (~75% of faces).

Therefore, we tested whether individual face salience (individual % of *first* fixations landing on faces) correlated with a general upper visual field bias. We defined the latter as the median elevation of *first* fixations towards images *not* containing a face (relative to central fixation and expressed in % image height). This was indeed the case (r = .49-.78 across samples, all $P < .05$; Supplementary Fig. 1b).

Given a correlation between individual face salience and a general bias towards the upper visual field, we wanted to test whether the salience bias *depended* on the visual field bias. Therefore, we tested whether individual differences in face salience persisted for the lower visual field, correlating the individual percentage of first fixations landing on faces in the upper visual field (UVF) with that landing on faces in the lower visual field (LVF). For this analysis, we defined UVF and LVF faces as those for which the median height of the pixel mask was in the upper and lower image half, respectively. Importantly, individual face salience was stable across the UVF and LVF, showing that it persisted independently of the UVF bias (r = .61-.87 across samples, all $P < .05$; Supplementary Fig. 1c).

Supplementary Figure



Supplementary Figure 1. Individual salience and visual field biases. (a) Distribution of different types of objects in image space across scenes. Notice the upwards bias of Faces. **(b)** Individual face salience significantly correlated with a general upper visual field bias in all four samples (i.e. with the elevation of first fixations towards images without a face; see Suppelemtary Methods above for details). **(c)**. Nevertheless, individual face salience persisted independent of this spatial bias. The individual proportion of first fixations landing in the upper and lower visual field (UVF and LVF) were highly correlated with each other.