# 1 Non-stimulated regions in early visual cortex encode the contents of

## 2 conscious visual perception

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## 14 Abstract

15 Predictions shape our perception. The theory of predictive processing poses that our brains make 16 sense of incoming sensory input by generating predictions, which are sent back from higher to lower 17 levels of the processing hierarchy. These predictions are based on our internal model of the world 18 and enable inferences about the hidden causes of the sensory input data. It has been proposed that conscious perception corresponds to the currently most probable internal model of the world. 19 20 Accordingly, predictions influencing conscious perception should be fed back from higher to lower 21 levels of the processing hierarchy. Here, we used functional magnetic resonance imaging (fMRI) and 22 multivoxel pattern analysis to show that non-stimulated regions of early visual areas contain 23 information about the conscious perception of an ambiguous visual stimulus. These results indicate that early sensory cortices in the human brain receive predictive feedback signals that reflect the 24 current contents of conscious perception. 25

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- 27

#### 28 Introduction

29 Predictions play an important role in perception<sup>1</sup>. According to the theory of predictive processing, our brains use an internal model of the world to make predictions that are fed back from higher to 30 31 lower levels of the processing hierarchy, thereby enabling inferences about the hidden causes of the 32 sensory input data<sup>2,3</sup>. This framework might provide the key to a neuroscientific account of 33 conscious perceptual experiences, one of the greatest challenges for theories of human brain 34 function. Within the framework of predictive processing, it has been proposed that conscious 35 perception corresponds to the currently most probable internal model of the world, that is, the 36 model that makes the best predictions about the incoming sensory data<sup>4</sup>. From this 37 conceptualization of conscious perception as reflecting a predictive model, it follows that predictions 38 generated by this model should be fed back from higher to lower levels of the processing hierarchy. 39 However, empirical studies supporting this idea are lacking. In the current study, we investigated 40 whether predictive feedback signals that reflect the current contents of conscious perception can be 41 observed in non-stimulated regions of human early visual cortex. Non-stimulated visual regions do 42 not receive any bottom-up stimulation, therefore any information in these regions must come from higher visual areas through feedback connections. This approach has successfully been used in 43 several previous studies, showing for example that feedback signals contain information not only 44 45 about which visual scene is presented<sup>5</sup>, but also about the spatial frequency of the scene<sup>6</sup>. High-field 46 fMRI studies have confirmed that decoded information in non-stimulated visual areas is due to 47 feedback mechanisms, as this information was present in superficial cortical layers, where feedback 48 signals arrive, and not the middle cortical layers, which process feedforward input<sup>7</sup>. Measuring 49 neural activity in regions of retinotopic visual cortex that do not receive feedforward input thus 50 provides an elegant way to isolate effects of predictive feedback signalling in the human brain. Here, 51 we used this method to probe whether the actual contents of conscious visual perception, too, 52 would be reflected by neural signals in non-stimulated regions of early visual cortex. We used an 53 ambiguous motion stimulus that gives rise to bistable perception (i.e., spontaneous alternations

54 between two perceptual states) and that was partially occluded. Decoding the two perceived visual 55 interpretations of the constant ambiguous stimulus, rather than two distinct stimuli, from non-56 stimulated visual regions would thus enable us to identify the presence of feedback signals reflecting 57 the current conscious percept.

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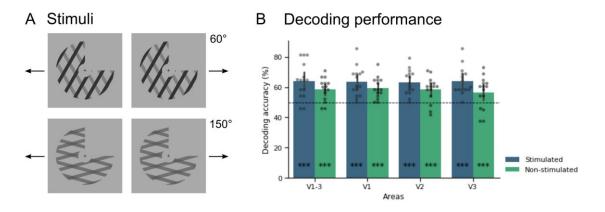
#### 59 Results

60 During fMRI scanning, participants were presented with ambiguous plaid-motion stimuli, composed 61 of two gratings moving in different directions (fig. 1A)<sup>8</sup>. The luminance of gratings and intersections 62 was chosen such that the stimuli could be perceived either as two gratings moving in different 63 directions (hereafter referred to as 'component perception') or as one pattern moving in the average direction of the two gratings ('pattern perception'). We used four different stimulus 64 65 configurations: The angle between the gratings could be 60° or 150°, and the average motion 66 direction was either leftward or rightward. Crucially, one quadrant of the stimulus was always 67 occluded, which allowed us to analyse fMRI signals in non-stimulated parts of retinotopic visual 68 areas.

69 Participants were asked to fixate the central fixation cross and indicate transitions between 70 component and pattern percepts via button presses. Trials in which no perceptual transitions were 71 reported were excluded. Eye tracking was performed and used for a control analysis, in which we 72 discarded runs with poor fixation performance. Functional localisers of the stimulated area, 73 occluded area, and border in between, as well as standard retinotopic mapping procedures, were 74 used to delineate regions of interest for early visual regions that responded to our stimuli and for 75 those representing the non-stimulated quadrant. For an additional control analysis, we used a V5 76 localiser to define hMT+/V5. We then applied multi-voxel pattern analysis using a linear support-77 vector-machine classifier to decode participants' perception from both stimulated and non-78 stimulated regions of visual cortex for each stimulus configuration, and averaged decoding

79 accuracies across conditions. Permutation tests were performed to determine significance (see

80 figure S1 and Supplementary Methods for details).



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Fig. 1. A) Ambiguous moving plaid stimuli were presented in four different stimulus configurations, which differed in the angle between the two component gratings (60° or 150°) and the overall motion direction of the resulting pattern (leftward or rightward). B) Classifier accuracy discriminating component and pattern perception across all stimulus configurations for stimulated and nonstimulated regions of early retinotopic areas. Error bars represent 95% confidence interval (Cl). \*p<0.05, \*\*p<0.01, \*\*\*p<0.001.

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89 As displayed in figure 1B, significant above-chance decoding performance was obtained for 90 both stimulated (64.1%, p<0.001) and non-stimulated (58.6%, p<0.001) regions of areas V1-V3 91 together. Decoding performance also reached significance in each of the retinotopic areas 92 separately (V1: 63.4% stimulated, 59.4% non-stimulated; V2: 63.3% stimulated, 58.4% non-93 stimulated; V3: 64% stimulated, 56.3% non-stimulated; all p<0.001). Our control analysis in which 94 runs with poor fixation performance were discarded led to comparable results (see fig. S2 and 95 Supplementary methods and results for details). Furthermore, when we corrected for the difference 96 in number of voxels between our stimulated and non-stimulated regions, we still obtained significant above-chance decoding results (see fig. S3 and Supplementary methods and results for 97 98 details).

99 According to the predictive processing theory, predictions about incoming sensory data are 100 fed back from higher visual areas. In the case of plaid motion stimuli, area hMT+/V5 has been 101 reported to be differentially activated during component vs. pattern motion<sup>9</sup> and is therefore a likely 102 candidate for the origin of feedback signalling. Here, we replicated the previous finding of greater 103 hMT+/V5 activity during component motion compared to pattern motion (fig. S5). More critically, 104 we additionally tested whether perceptual states could also be decoded from hMT+/V5 activity in a 105 subsample of participants, as this area should be able to represent the different percepts if it feeds 106 back predictions about these stimuli. This proof-of-concept analysis revealed that indeed the 107 component and pattern percepts could be decoded from hMT+/V5 with high accuracy (69.0%, p < 108 0.001, see fig. S4 and Supplementary methods and results for details).

109

### 110 Discussion

111 Our findings show that the current perceptual state during bistability can be decoded from fMRI signal patterns not only in stimulated early visual regions, which is in line with previous studies<sup>10</sup>, but 112 113 crucially also in non-stimulated retinotopic visual cortex, which did not receive any bottom-up input. 114 This suggests that non-stimulated regions of early visual cortex contain information not only about visual stimulation in the surrounding context, as previously shown<sup>5</sup>, but even about conscious 115 116 perception independent of visual stimulation per se. This is in line with current theories that model 117 bistable perception within the framework of predictive processing<sup>4,11</sup>. According to this view, 118 ambiguous stimuli (such as the bistable moving plaids used here) provide equally strong sensory 119 evidence for two different percepts, but the currently dominant percept establishes an implicit 120 prediction regarding the cause of the sensory input. This prediction is thought to stabilize the 121 current perceptual state through feedback from higher to lower hierarchical levels, while sensory 122 evidence for the currently suppressed perceptual interpretation elicits prediction errors that act to 123 destabilize the current percept, eventually leading to a perceptual change<sup>12,13</sup>. Here, we for the first 124 time provide evidence supporting the notion of feedback signalling of predictions in bistable

perception. Along these lines, we suggest that the percept-related information that we found in nonstimulated regions of early visual areas most likely arises from feedback signalling that originates from higher-level areas concerned with the computation of component vs. pattern motion perception, such as area hMT+/V5<sup>9</sup>. Our significant decoding results in hMT+/V5 support the idea that this area generates the predictions that are sent back to early visual areas, though future studies will have to provide direct causal evidence.

131 In conclusion, our current results provide compelling support for the notion that conscious 132 perception reflects an internal model that generates predictions about the current state of the 133 world, and that these predictions are fed back to the lowest levels of sensory processing to enable 134 inferences regarding the sensory input.

135

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139

#### 140 Author contributions

141 Conceptualisation, B.v.K. and P.S.; Methodology, B.v.K., G.W., and A.M.; Investigation, G.W. and

142 A.M.; Formal analysis, B.v.K.; Writing – Original draft, B.v.K.; Writing – Review & Editing, B.v.K., G.W.,

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#### 145 Declaration of interests

146 The authors declare no competing interests.

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#### **1** Supplementary methods

2

#### 3 Subjects

4 Sixteen participants took part in the study. Data from one participant had to be excluded, because 5 this participant reported only one percept in certain conditions, so that the other percept of the 6 respective condition could not be modelled (see fMRI analysis). This resulted in a final sample of 15 7 participants (age 18-33, M = 23.5 years, SD = 4.22, 5 male). None of the participants reported 8 current or previous neurological or psychiatric disorders. All had normal or corrected-to-normal 9 vision and were right-handed. Besides these general criteria, inclusion was based on performance in 10 a previous behavioural session with the same ambiguous plaid stimuli. An average perceptual phase 11 duration of > 4 s and a balance of at least 80/20 between the two percepts in each possible stimulus 12 configuration (pattern and component perception, see Stimuli) were required to be selected for the 13 fMRI session. The study was approved by the local ethics committee, and participants gave written 14 informed consent.

15

16 Stimuli

Plaid stimuli were created by superimposing two individual component square-wave gratings. The 17 18 stimuli were designed to be perceptually ambiguous, yielding bistable perception with spontaneous 19 alternations between perception of either the two components moving in different directions 20 ('component perception') or of one pattern moving in the average direction of the two gratings 21 ('pattern perception'). The angle between the components could be 60° or 150°, but for both angles 22 the average motion direction between the two gratings was horizontal, either leftward or rightward, resulting in four stimulus configurations (60° left, 60° right, 150° left, 150° right) that all elicited 23 24 bistability between component and pattern perception. fMRI results were pooled across these four 25 stimulus configurations, as they were not relevant to the purpose of the present study. The 26 individual gratings had a spatial frequency of 0.5 cycles per degree of visual angle and a duty cycle of 0.3. The term 'duty cycle' refers to the proportion of the width of the darker bars within one cycle of
the grating. The speed of the individual gratings was 1.3 cycles/s for the 60° stimuli, and 0.39
cycles/s for the 150° stimuli. The speed of the resulting plaid stimuli was 1.5 cycles/s for all stimulus
configurations.

31

32 The plaid stimuli were presented within a centred annulus with a diameter of 13° of visual angle. In the centre of the annulus, which had a diameter of 3°, a fixation cross was presented. The 33 34 background surrounding the stimuli had a luminance of 40 cd/m<sup>2</sup>. The luminance of the gratings of 35 the 150° stimuli was 14 cd/m<sup>2</sup>. For the 60° stimuli, the two component gratings differed in luminance: one grating had 2  $cd/m^2$ , the other 20  $cd/m^2$ . The luminance of the intersections of the 36 37 gratings was determined in pilot experiments that aimed at approximate equiprobability of 38 component and pattern perception for all stimulus types and resulted in an intersection luminance 39 of 9 cd/m<sup>2</sup> for the 150° stimuli and 2 cd/m<sup>2</sup> for the 60° stimuli.

40

#### 41 Procedure

42 The stimuli were presented on a screen at the end of the MRI scanner bore. Participants laid in the 43 scanner in supine position and viewed the stimuli on the screen through an angled mirror. They 44 were asked to fixate on the central fixation cross and report their percept (pattern or component 45 perception) by button presses. They had to report their percept as soon as the stimulus was 46 presented, and press a button anytime their percept changed. A pattern percept was reported with 47 the right index finger, and a component percept with the right middle finger. Each run comprised 48 eight trials, lasting 60 s each, during which a plaid stimulus was continuously presented in one of the 49 four stimulus configurations. Each trial was followed by a 10 s fixation interval, during which only the 50 fixation cross was presented. Each stimulus configuration was presented twice per run in 51 pseudorandomised order. There were six runs in total.

52

53 After the main experiment, two functional localisers were presented. The first was a stimulus 54 localiser. Here, each stimulus from the main experiment was presented for 12 s, followed by fixation 55 for 8 s, in a block-design. Different from the main experiment, participants were asked to fixate only and not report their perception. All conditions were presented four times in total. This functional 56 57 stimulus localiser allowed for selection of voxels that were activated by the stimuli used in the main 58 experiment. Furthermore, we used a functional localiser that mapped the non-stimulated region and 59 was designed to preclude any spill-over of activity from the stimulated region, similar to the localiser 60 of Smith & Muckli (2010). During this localiser, participants viewed contrast-reversing checkerboard 61 stimuli (4Hz), which were again presented for 12 s each, followed by 8 s of fixation. Each condition was repeated 8 times. The localiser contained 'surround stimuli', mapping the border between 62 63 stimulated and non-stimulated regions, and 'target stimuli', mapping the non-stimulated region. The 64 surround stimulus was presented at 0.5° of visual angle diagonally from the fixation cross, mapping 65 the outer 1° of the non-stimulated quadrant (see figure S1A). The checkerboard representing the non-stimulated quadrant, i.e. the target stimulus, was presented at 1° diagonally from the surround 66 67 stimulus (see figure S1B). Thus, the target region, from which voxels were selected for our decoding analysis of the non-stimulated quadrant, was ~2° away from the stimulated region. The scanning 68 69 session ended with a structural T1 scan (MPRAGE). Standard phase-encoded retinotopic mapping 70 was performed in a separate scanning session to define regions V1-3.

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Fig. S1. A) The surround stimulus mapping the border between stimulated and non-stimulated
regions. B) The target stimulus mapping the non-stimulated quadrant.

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## 76 *Scanning parameters*

77 Functional MRI data were acquired using a 3 T TIM Trio scanner (Siemens, Erlangen, Germany), 78 equipped with a 12-channel head-coil. A gradient echo EPI sequence was used (TR: 2 sec, TE: 30 79 msec, flip angle: 78°, voxel size 2.3 x 2.3 x 2.3 mm). Slices were oriented parallel to the calcarine 80 sulcus and acquired in descending order. A total of 135 volumes were acquired for each run of the 81 main experiment, 163 volumes for the stimulus localiser, 163 volumes for the non-stimulated 82 quadrant localiser, 123 volumes per run (3 in total) for the polar angle retinotopic mapping, and 102 83 volumes per run (3 in total) for eccentricity mapping. Anatomical images were obtained using an 84 MPRAGE sequence (TR: 1.9 sec, TE: 2.52 msec, flip angle: 9°).

85

#### 86 Eye movements

87 Eye movements were recorded with an iView Xtm MRI-LR system [SensoMotoric Instruments (SMI), Teltow, Germany] using a sampling rate of 50 Hz. Due to technical difficulties, no usable eye tracking 88 89 data were obtained for four participants, and for one run of a fifth participant. The eye tracking data were used in a control analysis to discard runs with poor fixation performance. To determine fixation 90 91 performance, a radius of 1.5° from fixation was defined as the fixation area. Eye movements beyond 92 this area were considered as outliers. Data were detrended and mean-corrected to determine the 93 number of these outliers, and runs in which eye movements extended beyond 1.5° of fixation in 94 more than 5% of all data points were excluded. A total of 10 runs distributed across 5 participants 95 were excluded in the control analysis based on eye tracking exclusion criteria.

96

97 fMRI analysis

98 The fMRI data were preprocessed and analysed using SPM12. First, the functional images were 99 realigned to correct for head motion, after which they were coregistered with the structural image 100 obtained in the same session. Then, both functional and structural images were coregistered with 101 the structural image obtained in the retinotopy session. No normalisation or smoothing was applied, 102 as is common for studies using MVPA.

A general linear model (GLM) was set up with regressors modelling the participants' percepts (pattern vs components) of each condition, resulting in eight regressors of interest. Motion parameters as well as a regressor modelling fixation in between trials were included as regressors of no interest. If participants reported only one percept for a certain condition, the other percept of that condition could not be modelled in that run; therefore, such runs were excluded. This affected all runs from one participant, and another 7 runs distributed across 3 participants.

109

#### 110 ROI definition

111 Regions of interest (ROIs) were defined with similar methods as those used by Smith & Muckli 112 (2010). First, regions V1-V3 were defined using standard retinotopic mapping procedures. Within 113 regions V1-3, only the voxels that showed significant positive response to the stimulated region (t-114 contrast stimulus > fixation, p < 0.01 uncorr.) in our stimulus localiser were selected. For the non-115 stimulated region, the following procedure was used. First, only voxels that showed significant 116 positive response to the target region (t-contrast stimulus > fixation, p < 0.01 uncorr.) were selected. 117 Then, in order to ensure that these voxels were not also responsive to the stimulated region, we 118 further selected only the voxels that met these criteria: significant positive response to the non-119 stimulated target area alone (t > 1.65, p < 0.01 uncorr.), no significant response to the stimulated 120 area alone (t > 1.65, p < 0.01 uncorr.), and no significant response to the surround region (t > 1.65, p121 < 0.01 uncorr.).

122 The stimulated ROIs were naturally larger than the non-stimulated ROIs, as the stimulus spanned 123 three quadrants compared to one occluded quadrant. Furthermore, our strict criteria for selecting 124 non-stimulated voxels outlined above meant we only selected a small sample of the voxels 125 corresponding to the occluded quadrant. To correct for potential biases induced by this difference in 126 ROI size, we performed an additional control analysis with smaller stimulated ROIs that had the 127 same number of voxels as their non-stimulated counterpart ROI. These ROIs were generated by 128 manually selecting voxels corresponding to the stimulus quadrant immediately opposite the 129 occluded quadrant, in our case the quadrant in the upper left visual field. As such, we selected 130 voxels in the right hemisphere below the calcarine sulcus. From these voxels, we randomly selected 131 *n* voxels, with *n* being the number of voxels of the non-stimulated ROI for that particular visual area 132 (V1-3) and participant. For two participants, not enough voxels were available in the respective stimulated quadrant of V1 to match the number of voxels from the non-stimulated V1 ROI. For these 133 134 two participants, we therefore used all the voxels available in the stimulated guadrant and thus had 135 slightly less voxels in stimulated V1 ROI compared to the non-stimulated V1 ROI (for one participant 136 12 stimulated voxels vs 15 non-stimulated voxels, for the other participant 6 stimulated voxels vs 24 137 non-stimulated voxels).

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139 MVPA

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141 Multi-voxel pattern analysis (MVPA) was performed using The Decoding Toolbox (Hebart, Görgen, & 142 Haynes, 2015), which implements LibSVM software (http://www.csie.ntu.edu.tw/wcjlin/libsv). A 143 linear support vector machine was trained to discriminate pattern from component percepts based 144 on the beta values resulting from the GLM. This classification was performed for each stimulus 145 configuration separately. Classifier performance was tested using a leave-one-run-out cross-146 validation approach. Training was carried out on all but one run, which served as the test data. This 147 was repeated until all runs had served as a test run once. The decoding accuracy was averaged 148 across cross-validations and then across conditions. Permutation testing was conducted to 149 determine the significance at the group level as described by Stelzer, Chen, & Turner (2013). In brief,

we provided the classifier with all possible combinations of shuffled label assignments for each participant and performed the decoding procedure for each label assignment. Then, we randomly selected one of these decoding accuracies from each participant and calculated the mean decoding accuracy. This procedure of random selection and calculation of mean decoding accuracy was repeated 10,000 to generate a distribution of decoding accuracies. We then used a cut-off of 95% to determine significance of our results.

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157 Supplementary results

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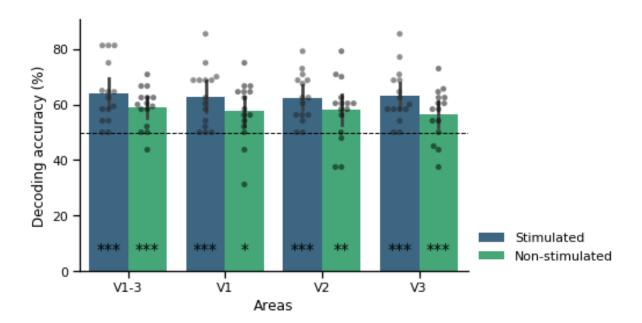
159 Phase durations

The mean perceptual phase duration of the 60° stimuli (averaged across leftward and rightward moving stimuli) was 7.4 s for components (SD = 8.6) and 9.9 s for patterns (SD = 4.6). For the 150° stimuli, mean phase duration for components was 8.2 s (SD = 7.5) and for patterns 4.9 s (SD = 1.7).

163

#### 164 *Control analysis discarding runs with poor fixation performance*

Overall fixation accuracy across all participants was 97.3%. Despite this high accuracy, we performed a control analysis discarding runs with fixations more than 5% outside of our fixation ROI. As displayed in figure S2, significant above-chance decoding performance was obtained for both stimulated (64.0%, p<0.001) and non-stimulated (58.9%, p<0.001) regions of areas V1-V3 together. Decoding performance also reached significance in each of the retinotopic areas separately (V1: 62.9% stimulated, p<0.001, 57.8% non-stimulated, p=0.015; V2: 62.4% stimulated, p<0.001, 58.0% non-stimulated, p = 0.007; V3: 63.0% stimulated, p<0.001, 56.7% non-stimulated, p<0.001). bioRxiv preprint doi: https://doi.org/10.1101/2020.11.13.381269; this version posted November 15, 2020. The copyright holder for this preprint (which was not certified by peer review) is the author/funder. All rights reserved. No reuse allowed without permission.



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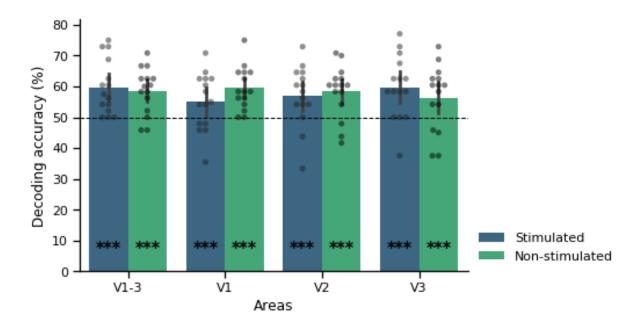
Fig. S2. Classifier accuracy discriminating component and pattern perception across all stimulus
configurations for stimulated and non-stimulated regions of early retinotopic areas. In this analysis,
runs with poor fixation performance were excluded. Error bars represent 95% confidence interval
(Cl). \*p<0.05, \*\*p<0.01, \*\*\*p<0.001.</li>

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178 Control analysis correcting for the difference in number of voxels between stimulated and non-179 stimulated ROIs

In this analysis, we decoded from stimulated and non-stimulated ROIs that were matched in size. As
displayed in figure S2, significant above-chance decoding performance was obtained for both
stimulated (60.9%, p<0.001) and non-stimulated (58.6%, p<0.001) regions of areas V1-V3 together.</li>
Decoding performance also reached significance in each of the retinotopic areas separately (V1:
55.2% stimulated, 59.4% non-stimulated; V2: 56.5% stimulated, 58.4% non-stimulated; V3: 59.2%
stimulated, 56.3% non-stimulated, all p<0.001).</li>

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Fig. S3. Classifier accuracy discriminating component and pattern perception across all stimulus
configurations for stimulated and non-stimulated regions of early retinotopic areas. In this analysis,
the number of voxels in stimulated V1 ROIs matched those of non-stimulated V1 ROIs. Error bars
represent 95% confidence interval (CI). \*p<0.05, \*\*p<0.01, \*\*\*p<0.001.</li>

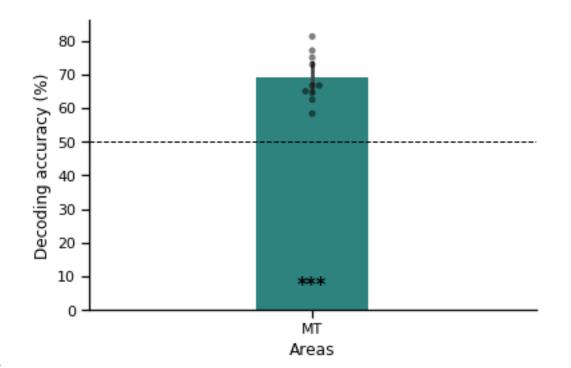
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193 Control analysis decoding from hMT+/V5

194 hMT+/V5 localiser data were available for 10 of our subjects. From these hMT+/V5 ROIs, we could

decode component vs pattern percepts significantly above chance (69.0%, p < 0.001; see figure S4).

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Fig. S4. Classifier accuracy discriminating component and pattern perception across all stimulus
 configurations for area hMT+/V5. Error bars represent 95% confidence interval (CI). \*p<0.05,</li>
 \*\*p<0.01, \*\*\*p<0.001.</li>

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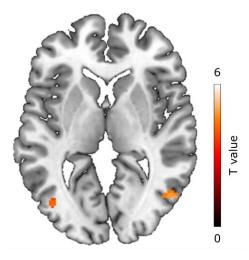
201 Control analysis testing for non-specific effects in early visual cortex

202 In order to test whether non-specific effects related to the change in perception and resulting 203 decision making influenced our results, we performed a univariate analysis contrasting component 204 with pattern percepts and vice versa. To this end, data preprocessing included coregistration of 205 functional and anatomical images, normalisation to MNI space and smoothing with an 8mm full 206 width at half maximum kernel. The same GLM was run as was used for our MVPA analysis. T-207 contrasts of components > patterns and patterns > components were passed on to group level T-208 tests. An initial voxel threshold of p < 0.001 uncorrected was used with FWE cluster correction to 209 determine significance.

210 Since it has been shown that components elicit more activity in hMT+/V5 than patterns (Castelo-211 Branco et al., 2002), we expected clusters in hMT+/V5 for the contrast components > patterns. As

such we performed a ROI analysis using an anatomical mask of hMT+/V5 from the anatomy toolbox.
This contrast indeed revealed clusters in bilateral hMT+/V5, supporting the results by Castelo-Branco
et al. (2002). No other clusters reached significance. The reverse contrast, patterns > components,
also yielded no significant clusters. These results suggest that no non-specific effects influenced our

216 decoding results in visual cortex.



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Fig. S5. Univariate analysis showing increased activity for components compared to patterns in bilateral hMT+/V5. ROI analysis with anatomical hMT+/V5 ROI from the anatomy toolbox using an initial voxel threshold of p < 0.001, uncorrected, showing FWE cluster corrected results.

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