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### <u>Title:</u>

### Distinct neural components of visually guided grasping during planning and execution

### Abbreviated title:

Neural components of visually guided grasping

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### Author contributions:

All authors conceived and designed the study. LKK collected the data. LKK, KS, and GM analyzed the data with guidance from JCC. LKK, GM, JCC and RWF wrote the manuscript.

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### 1 Abstract

2 Selecting suitable grasps on three-dimensional objects is a challenging visuomotor 3 computation, which involves combining information about an object (e.g., its shape, 4 size, and mass) with information about the actor's body (e.g., the optimal grasp 5 aperture and hand posture for comfortable manipulation). Here we used functional 6 magnetic resonance imaging to investigate brain networks associated with these 7 distinct aspects during grasp planning and execution. Human participants 8 of either sex viewed and then executed preselected grasps on L-shaped objects made of wood and/or brass. By leveraging a computational approach that accurately 9 10 predicts human grasp locations, we selected grasp points that disentangled the role 11 of multiple grasp-relevant factors: grasp axis, grasp size, and object mass. Representational Similarity Analysis revealed that grasp axis was encoded along 12 13 dorsal-stream regions during grasp planning. Grasp size was first encoded in 14 ventral-stream areas during grasp planning, then in premotor regions during grasp 15 execution. Object mass was encoded in ventral-stream and (pre)motor regions only during grasp execution. Premotor regions further encoded visual predictions of grasp 16 17 comfort, whereas the ventral stream encoded grasp comfort during execution, 18 suggesting its involvement in haptic evaluation. These shifts in neural 19 representations thus capture the sensorimotor transformations that allow humans to grasp objects. 20

### 22 Significance Statement

23 Grasping requires integrating object properties with constraints on hand and arm 24 postures. Using a computational approach that accurately predicts human grasp 25 locations by combining such constraints, we selected grasps on objects that disentangled the relative contributions of object mass, grasp size, and grasp axis 26 during grasp planning and execution in a neuroimaging study. Our findings reveal a 27 28 greater role of dorsal-stream visuomotor areas during grasp planning, and 29 surprisingly, increasing ventral stream engagement during execution. We propose that during planning, visuomotor representations initially encode grasp axis and size. 30 Perceptual representations of object material properties become more relevant 31 32 instead as the hand approaches the object and motor programs are refined with estimates of the grip forces required to successfully lift the object. 33

### 35 Introduction

36 Grasping is one of the most frequent and essential everyday actions performed by 37 humans and other primates (Betti et al., 2021), yet planning effective grasps is 38 computationally challenging. Successful grasping requires identifying object 39 properties including shape, orientation and mass, and considering how these interact with the capabilities of our hands (Fabbri et al., 2016; Maiello et al., 2019, 2021; 40 Klein, Maiello et al., 2020). Whether an object is large or small, heavy or light, 41 42 determines how wide we open our hands to grasp it and how much force we apply to lift it (Johansson and Westling, 1988; Cesari and Newell, 1999). Such grasp-relevant 43 object properties, including weight, mass distribution, and surface friction can often 44 be inferred visually before initiating actions (Fleming, 2017; Klein et al., 2021). 45

A recent computational model accurately predicts precision-grip grasp locations on 46 3D objects of varying shape and non-uniform mass (Klein, Maiello et al., 2020). The 47 model combines multiple constraints related to properties of the object and the 48 49 effector, such as the torque associated with different grasps and the actor's natural 50 grasp axis. However, it remains unclear which brain networks are involved in computing specific grasping constraints. Moreover, it is unknown whether all 51 constraints are estimated during grasp planning (i.e., before action initiation; Gallivan 52 53 et al., 2013, 2019) or whether some aspects are computed during action execution, 54 allowing the actor to refine grasp parameters on-line before or during contact with 55 the object. Here, we ask how information gets combined to evaluate and then execute grasps. While many previous studies have investigated the effects of 56 individual attributes, during either grasp planning or execution, here we consider how 57 multiple factors combine, and compare both planning and execution. 58

Previous studies show that grasp-relevant representations are distributed across 59 ventral and dorsal visual processing streams. Shape is represented throughout both 60 61 streams (Sereno et al., 2002; Orban et al., 2006; Konen and Kastner, 2008; Orban, 2011), with dorsal representations emphasizing information required for grasp 62 planning (Srivastava et al., 2009). For example, dorsomedial area V6A-located in 63 human superior parieto-occipital cortex (SPOC)-is involved in selecting hand 64 65 orientation given object shape (Fattori et al., 2004, 2009, 2010; Monaco et al., 2011). Visual representations of material properties—also crucial for grasping—have been 66 identified predominantly in ventral regions such as lateral occipital cortex (LOC), the 67 posterior fusiform sulcus (pFS), and parahippocampal place area (PPA; Cant and 68 Goodale, 2011; Hiramatsu et al., 2011; Gallivan et al., 2014; Goda et al., 2014, 69 70 2016). Brain regions that transform these disparate visual representations into 71 appropriate motor codes include Anterior Intraparietal Sulcus (aIPS), Ventral Premotor Cortex (PMv), Dorsal Premotor Cortex (PMd), and primary motor cortex 72 (M1). Primate neurophysiology suggests that PMv (primate Area F5) encodes grip 73 74 configuration (Murata et al., 1997; Raos et al., 2006; Theys et al., 2012), while PMd 75 (primate Area F2) encodes grip/wrist orientation (Raos et al., 2004). Both regions exhibit strong connections with aIPS, which could play a key role in linking visual 76 representations-including those in ventral stream regions (Borra et al., 2008)-to 77 motor commands sent to the hand through M1 (Murata et al., 2000; Janssen and 78 Scherberger, 2015). 79

How information flows and is combined across this complex network of brain regions is far from understood. We therefore sought to identify cortical regions associated with distinct components of grasping and tested their relative importance during grasp planning and execution. To disentangle grasping constraints, we used our

model (Maiello et al., 2021) to select grasps that placed different constraints in 84 conflict. For example, a selected grasp could be near optimal in terms of the required 85 86 hand axis, but sub-optimal in terms of grasp aperture. We then measured functional magnetic resonance imaging (fMRI) blood-oxygen-level-dependent (BOLD) activity, 87 during planning and execution of these preselected grasps. Combining this model-88 guided approach with representational similarity analysis (RSA; Kriegeskorte, 2008) 89 90 let us tease apart the relative contributions of object mass, grasp size, and grasp 91 axis, at different stages of grasping.

92

### 93 Materials and Methods

94 Participants. Analyses utilized data from 21 participants (13 female, mean [range] 95 age: 25.5 [18-33]) recruited from the University of Western Ontario. Data from two 96 additional participants were excluded due to excessive head motion. All participants 97 had normal or corrected-to-normal vision and were fully right-handed as measured 98 by the Edinburgh Handedness Inventory. Informed consent was given prior to the experiment. The study was approved by the Health Sciences Research Ethics Board 99 at the University of Western Ontario and followed the principles in the 6<sup>th</sup> revision of 100 the Declaration of Helsinki (2008). Participants were instructed on how to perform 101 the experimental task before entering the MRI room, yet remained naïve with respect 102 to the study's hypotheses. Participants were financially compensated at a rate of 103 104 C\$25/hour.

Setup. A schematic of our setup is shown in Figure 1A. Each participant lay supine 105 inside the MRI scanner with their head placed in a head coil tilted by ~30° to allow 106 direct viewing of real stimulus objects placed in front of them. Below the head we 107 108 positioned the bottom 20 channels of a 32-channel head coil and we suspended a 4channel flex coil via loc-line (Lockwood Products, Inc.) over the forehead. A black 109 wooden platform, placed above a participant's hip, enabled the presentation of real 110 objects that participants were required to grasp, lift, and set back down using their 111 right hand. The platform's flat surface was tilted by ~15° towards a participant in 112 113 order to maximize comfort and visibility. Objects were placed on a black cardboard target ramp (Figure 1A: "Ramp", dimensions: 15 x 5 x 13 cm) on top of the platform 114 that created a level surface which prevented objects from tipping over. The objects' 115 exact placement was adjusted such that all required movements were possible and 116 117 comfortable. Between trials, a participant's right hand rested on a button at a start

position on the table's lower right side. The button monitored movement start and 118 end times. A participant's upper right arm was strapped to their upper body and the 119 120 MRI table using a hemi-cylindrical brace (not displayed in Figure 1A). This prevented shoulder and head movements, thus minimizing movement artefacts while 121 enabling reach-to-grasp movements through elbow and wrist rotations. A small red 122 LED fixation target was placed above and at a slightly closer depth location than the 123 124 object to control for eye movements. Participants were required to maintain fixation on this target at all times during scanning. An MR-compatible camera was positioned 125 on the left side of the head coil to record the participant's actions. Videos of the runs 126 were screened offline and trials containing errors were excluded from further 127 128 analyses. A total of 22 error trials were excluded, 18 of which occurred in one run 129 where the participant erroneously grasped the objects during the planning phase.

Two bright LEDs illuminated the workplace for the duration of the planning and 130 131 execution phases of each trial, one was mounted on the head coil and the other was taped to the ceiling of the bore. Another LED was taped to the outside of the bore 132 and was only visible to the experimenter to cue the extraction and placement of the 133 objects. The objects were kept on a table next to the MRI-scanner, on which three 134 135 LEDs cued the experimenter on which object to place inside the scanner. Participants wore MR-safe headphones through which task instructions were relayed 136 on every trial. The LEDs and headphones were controlled by a MATLAB script on a 137 138 PC that interfaced with the MRI scanner. Triggers were received from the scanner at the start of every volume acquisition. All other lights in the MRI room were turned off 139 140 and any other potential light sources and windows were covered so that no other light could illuminate the participant's workspace. 141

Stimuli. Stimuli were three L-shaped objects of the same size, created from seven 142 blocks (cubes of 2.5 cm side length). One object was constructed with seven cubes 143 144 of beech wood (object weight: 67g), whereas the other two were both constructed of four brass and three wooden cubes (object weight: 557g). We performed pilot testing 145 to ensure that the objects and their movements did not evoke artifacts related to the 146 movement of masses within the scanner (Barry et al., 2010). Specifically, we placed 147 148 a spherical MRI phantom (immobile mass) in the scanner and collected fMRI data while the experimenter placed and removed the objects, as they would in the actual 149 experiment. Functional time courses were carefully examined to ensure that no 150 artifacts were observed (such as spikes or abrupt changes in signal at the time of 151 action, e.g., Culham, 2006; Singhal et al., 2013). The two identical wood-brass 152 153 objects were positioned in two different orientations, one with the brass "arm" pointing up (see Figure 1F: "BrassUp"), the other with the brass arm lying down 154 155 ("BrassDown"). In a slow event-related fMRI design, on each trial participants directly viewed, grasped, and lifted an object placed on a platform. 156

**Task.** Participants performed three distinct grasps per object, each grasp marked on 157 158 the objects with coloured stickers during the experiment. The colours were clearly 159 distinguishable inside the scanner and served to cue participants about which grasp to perform. Participants were instructed to perform three-digit grasps with their right 160 hand, by placing the thumb in opposition to index and middle fingers. This grasp was 161 162 similar to the precision grip grasps employed in our previous work (Maiello et al., 2019, 2021; Klein, Maiello et al., 2020; Klein et al., 2021), but ensured participants 163 could apply sufficient grip force to lift all objects to a height of approximately 2 cm 164 165 above the platform. Grasp contact locations for the index and thumb were selected in 166 order to produce a set of uncorrelated-and thus linearly independent-

representational dissimilarity matrices (RDMs) for the three grasp factors 167 investigated: grasp axis, grasp size, and object mass. Specifically, grasps could be 168 169 rotated 45° either clockwise or counter clockwise around the vertical axis, and could require small (2.5 cm) or large (7.5 cm) grip apertures. In pilot testing we further 170 refined the positioning of the objects and grasps within the magnetic field of the MRI 171 scanner to avoid the forming of eddy currents within the brass parts of the objects 172 173 which could hinder participants from executing the grasps. The complete set of grasp conditions is shown in Figure 1C. 174

### 175 Experimental Design and Statistical Analysis

176 fMRI Experimental Procedure. We employed a slow event-related fMRI design with trials spaced every 23-31 s. Participants underwent 4 experimental runs in which 177 they performed each combination of 3 objects x 3 grasps twice per run (18 trials x 178 179 run, 72 trials total) in a pseudorandom order to minimize trial order effects (van Polanen and Davare, 2015a; Maiello et al., 2018; van Polanen et al., 2020). The 180 181 sequence of events occurring on each trial is schematized in Figure 1B. Prior to each trial, the experimenter was first cued on which object to place inside the 182 scanner. The experimenter placed the object on the ramp. At trial onset, the 183 illumination LEDs turned on and over the headphones the participant heard the 184 instruction "plan", immediately followed by the auditory cue specifying which grasp to 185 execute. The auditory cue was "blue", "green", or "red", which corresponded to 186 coloured stickers marking the grasp locations on the objects. The duration of the 187 planning phase of the task was randomly selected to be 6, 8, 10, or 12 s. During this 188 time, the participant was required to hold still and mentally prepare to grasp the 189 190 object at the cued location. Following previous research (Gallivan et al., 2014, 2015), we employed a variable delay between cue and movement onset to distinguish 191

sustained planning-related neural activity from the movement-execution response 192 accompanying action initiation. It is important to note that what we refer to with the 193 194 term "action planning", is a sustained action planning, pre-viewing phase in which participants are thinking about how to execute the movement and must thus access 195 mental representations of the object and task. In this kind of delayed action task, 196 previous work has demonstrated that dorsal-stream areas plan and maintain action 197 198 goals (Singhal et al., 2013). We specifically do not mean the purely feedforward movement planning which occurs only a few hundred milliseconds prior to movement 199 initiation (e.g., Westwood and Goodale, 2003), because it is unfeasible to investigate 200 neural signals at this time scale though fMRI BOLD activity. 201

Once the planning phase ended, "lift" was played over headphones to cue the 202 203 participant to execute the grasp. During the execution phase of the task, the participant had 7 s to reach, grasp, and lift the object straight up by approximately 2 204 205 cm, place it back down on the target ramp, and return their hand to the start position. The illumination LEDs turned off, and the participant waited for a 10-12 s intertrial 206 interval (ITI) for the next trial to begin. During the ITI the experimenter removed the 207 208 object and placed the next one before the onset of the following trial. We note that 209 we did not include a passive preview phase in our trial design, because we have repeatedly shown in previous studies that action intentions cannot be decoded from 210 neural activity recorded during passive stimulus preview (Gallivan et al., 2011, 211 212 2013b, 2013a).

Participants were instructed about the task, familiarized themselves with the objects, and practiced the grasps outside of the MRI room for about 5 minutes prior to the experiment. Once participants were strapped into the setup, they practiced all grasps again, thus ensuring that they could comfortably grasp each object.

**Grasp Comfort Ratings.** At the end of the fMRI experiment, participants remained positioned in the scanner and performed a short rating task. Participants were asked to perform one more time each of the nine grasp conditions. For each grasp, participants verbally reported how comfortable the grasp was on a scale of 1-10 (1 being highly uncomfortable and 10 being highly comfortable). Verbal ratings were manually recorded by the experimenter.

Analyses. Data analyses were conducted using Brain Voyager 20.0 (BV20) and
21.4 (BV21.4) software packages (Brain Innovation, Maastricht, The Netherlands),
as well as MATLAB version R2019b.

226 fMRI data acquisition. Imaging was performed using a 3-Tesla Siemens Prisma Fit MRI scanner at the Robarts Research Institute at the University of Western Ontario. 227 Functional MRI volumes were acquired using a T2\*-weighted, single-shot, gradient-228 229 echo echo-planar imaging acquisition sequence. Functional scanning parameters were: time to repetition (TR) = 1000 ms; time to echo (TE) = 30 ms; field of view = 230 231 210 x 210 mm in-plane; 48 axial 3-mm slices; voxel resolution = 3-mm isotropic; flip angle = 40°; and multi-band factor = 4. Anatomical scans were acquired using a T1-232 weighted MPRAGE sequence with parameters: TR = 2300 ms; field of view = 248 x 233 256 mm in-plane, 176 sagittal 1-mm slices; flip angle = 8°; 1-mm isotropic voxels. 234

fMRI data preprocessing. Brain imaging data were preprocessed using the BV20 Preprocessing Workflow. First, we performed Inhomogeneity Correction and extracted the brain from the skull. We then coregistered the functional images to the anatomical images, and normalized anatomical and functional data to Montreal Neurological Institute (MNI) space. Functional scans underwent motion correction and high-pass temporal filtering (to remove frequencies below 3 cycles/run). No slice scan time correction and no spatial smoothing were applied.

**General linear model.** Data were further processed with a random-effects general linear model that included one predictor for each of the 18 conditions (3 grasp locations x 3 objects x 2 phases [planning vs. execution]) convolved with the default Brain Voyager "two-gamma" hemodynamic response function (Friston et al., 1998) and aligned to trial onset. As predictors of no interest, we included the 6 motion parameters (x, y, and z translations and rotations) resulting from the 3D motion correction.

Definition of Regions of Interest. We investigated a targeted range of regions of 249 250 interest (ROIs). The locations of these ROIs are shown in Figure 1H; the criteria used to define the regions and their MNI coordinates are given in Table 1. ROIs were 251 252 selected from the literature as regions most likely specialized in the components of 253 visually guided grasping investigated in our study. These included primary visual cortex V1, areas LO, pFS, and PPA within the ventral visual stream 254 (occipitotemporal cortex), areas SPOC, aIPS, PMv, PMd within the dorsal visual 255 stream (occipitoparietal and premotor cortex), and primary sensorimotor cortex 256 M1/S1. 257

Primary visual cortex (V1) was included because it represents the first stage of cortical visual processing upon which all subsequent visuomotor computations rely. Primary motor area M1 was included instead as the final stage of processing, where motor commands are generated and sent to the arm and hand. In our study, however, we refer to this ROI as primary motor and somatosensory cortex M1/S1, because our volumetric data do not allow us to distinguish between the two banks of the central sulcus along which motor and somatosensory regions lie.

We next selected regions believed to perform the sensorimotor transformations that link visual inputs to motor outputs. The dorsal visual stream is thought to be

predominantly specialized for visually guided actions, whereas the ventral stream mostly specializes in visual object recognition (Goodale and Milner, 1992; Culham et al., 2003; Cavina-Pratesi et al., 2007; Vaziri-Pashkam and Xu, 2017). Nevertheless, significant crosstalk occurs between these streams (Budisavljevic et al., 2018), and visual representations of object material properties have been found predominantly in ventral regions. We therefore selected areas across both dorsal and ventral visual streams that would encode grasp axis, grasp size, and object mass.

274 We expected grasp axis could be encoded in dorsal stream regions SPOC (Fattori et 275 al., 2004, 2009, 2010; Monaco et al., 2011), aIPS (Taubert et al., 2010), PMv (Murata et al., 1997; Raos et al., 2006; Theys et al., 2012), and PMd (Raos et al., 276 2004). We expected grasp size to be encoded in dorsal stream regions SPOC, aIPS 277 (Monaco et al., 2015), PMd (Monaco et al., 2015), and PMv (Murata et al., 1997; 278 Raos et al., 2006; Theys et al., 2012), and ventral stream region LO (Monaco et al., 279 280 2015). We expected visual estimates of object mass to be encoded in ventral stream regions LO, pFS, and PPA (Cant and Goodale, 2011; Hiramatsu et al., 2011; 281 Gallivan et al., 2014; Goda et al., 2014, 2016). We further hypothesised that the 282 283 network formed by aIPS, PMv, and PMd might play a role in linking ventral stream 284 representations of object mass to the motor commands generated and sent to the hand through M1 (Murata et al., 2000; Borra et al., 2008; Davare et al., 2009, 2010, 285 2011; Janssen and Scherberger, 2015; van Polanen and Davare, 2015b; 286 287 Schwettmann et al., 2019; Schmid et al., 2021).

It should be noted that we do not expect the set of ROIs investigated here to be the exhaustive set of regions involved in visually-guided grasping. For example, subcortical regions are also likely to play a role (Nowak et al., 2007; Prodoehl et al., 2009; Cavina-Pratesi et al., 2018). However, cortical and subcortical structures

require different imaging protocols (De Hollander et al., 2017; Miletić et al., 2020), 292 and the small size and heterogeneity of subcortical structures also require different 293 294 normalization, co-registration, and alignment techniques than those used in the cortex (e.g. Diedrichsen et al., 2010). Moreover, adding further ROIs would reduce 295 statistical power when correcting for multiple comparisons. We thus chose to focus 296 on a constrained set of cortical regions for which we had a-priori hypotheses 297 298 regarding their involvement in the aspects of visually-guided grasping investigated here. Nevertheless, we hope that exploratory analyses on our open access data may 299 guide future studies mapping out the distributed neural circuitry involved in visually-300 guided grasping. 301

302 Figure 1H shows our selected ROIs as volumes within the Colin27 template brain. 303 To locate all left hemisphere ROIs (except V1) in a standardized fashion we searched the automated meta-analysis website neurosynth.org (Yarkoni et al., 2011) 304 305 for key words (**Table 1**), which yielded volumetric statistical maps. Visual inspection of the maps allowed us to locate the ROIs we had pre-selected based on a 306 combination of activation peaks, anatomical criteria, and expected location from the 307 relevant literature. For example, aIPS was selected based on the hotspot for 308 309 "grasping" nearest to the intersection of the intraparietal and postcentral sulci (Culham et al., 2003). Spherical ROIs of 15-mm diameter, centred on the peak voxel, 310 were selected for all regions except V1. Because Neurosynth is based on a meta-311 analysis of published studies, search terms like "V1" would be biased to the typical 312 retinotopic locations employed in the literature and likely skewed towards the foveal 313 314 representation (whereas the objects and hand would have been viewed across a larger expanse within the lower visual field). As such, we defined V1 in the left 315 hemisphere's V1 using the (Wang et al., 2015) atlas, which mapped retinotopic 316

cortex +/-  $\sim$ 15° from the fovea. **Table 1** presents an overview of our ROI selection, where we list all our Neurosynth-extracted ROIs with their peak coordinates, search terms and download dates. We also share our ROIs (in MNI space) in the *nifti* format (doi upon acceptance).

321 Representational Similarity Analysis. The analysis of activation patterns within the selected ROIs was performed using multivoxel pattern analysis, specifically 322 representational similarity analysis (RSA) (Kriegeskorte, 2008; Kriegeskorte et al., 323 2008). An activation pattern corresponded to the set of normalized  $\beta$ -weight 324 325 estimates of the blood oxygenation level-dependent (BOLD) response of all voxels within a specific ROI for a specific condition. To construct representational 326 dissimilarity matrices (RDMs) for each ROI, we computed the dissimilarity between 327 328 activation patterns for each condition. Dissimilarity was defined as 1-r, where r was the Pearson correlation coefficient. RDMs were computed separately from both 329 330 grasp planning and grasp execution phases. These neural RDMs computed were then correlated to model RDMs (Figure 1D,E,F) to test whether neural 331 representations encoded grasp axis, grasp size, and object mass. To estimate 332 maximum correlation values expected in each region given the between-participant 333 334 variability, we computed the upper and lower bounds of the noise ceiling. The upper bound of the noise ceiling was computed as the average correlation of each 335 participant's RDMs with the average RDM in each ROI. The lower bound of the noise 336 337 ceiling was computed by correlating each participant's RDMs with the average of the other participants' RDMs. All correlations were performed between upper triangular 338 339 portions of the RDMs excluding the diagonal. We then used one-tailed Wilcoxon signed rank tests to determine whether these correlations were significantly >0 within 340 341 each ROI. We set statistical significance at p<.05 and applied false discovery rate

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342 (FDR) correction for multiple comparisons following (Benjamini and Hochberg,343 1995).

To visualize the representational structure of the neural activity patterns within grasp 344 345 planning and grasp execution phases, we first averaged RDMs across participants in each ROI and task phase. We then correlated average RDMs across ROIs within 346 each phase and used hierarchical clustering and multidimensional scaling to 347 visualize representational similarities across brain regions. We also correlated 348 349 average RDMs across ROIs and across planning and execution phases. Statistically 350 significant correlations (p<.05 with Bonferroni correction) are shown also as topological connectivity plots (within-phase data) and as Sankey diagram (between-351 phase data). 352

Grasp Comfort Ratings. Grasp comfort ratings were analysed using simple t-tests 353 354 to assess whether ratings varied across different grasp axes, grasp sizes, or object mass. The difference between ratings for each condition was then used to create 355 356 grasp comfort RDMs for each participant. Grasp comfort RDMs were correlated to model RDMs to further test how strongly grasp comfort corresponded to grasp axis, 357 grasp size, and object mass. To search for brain regions that might encode grasp 358 comfort, the average grasp comfort RDM was correlated to neural RDMs following 359 RSA as described above. 360

### 361 **Results**

362 Participants in a 3-Tesla MRI scanner were presented with physical 3D objects on 363 which predefined grasp locations were shown (Figure 1A). On each trial, 364 participants first planned how to grasp the objects (planning phase, Figure 1B) and 365 then executed the grasps (execution phase). We designed objects and grasp 366 locations to produce a set of nine distinct conditions (Figure 1C) that would differentiate three components of grasping: the grasp axis (i.e., orientation), the 367 grasp size (i.e., the grip aperture), and object mass. By computing pairwise 368 369 distances between all conditions for each of these grasp-relevant dimensions, we constructed one representational dissimilarity matrix (RDM) for each component 370 371 (Figure 1D-F)—these were uncorrelated across conditions. In each brain region of interest (ROI) tested in the study (Figure 1H), brain-activity patterns elicited by each 372 373 condition were compared to each other via Pearson correlation to construct brain 374 RDMs. Figure 1G shows one such RDM computed from brain region PMv for one 375 example participant during the planning phase. In this participant, this area appeared to strongly encode grasp axis. 376

How grasp-relevant neural representations develop across the grasp network. 377 Figure 2A shows average neural RDMs computed throughout the network of 378 379 visuomotor brain regions we investigated. ROIs were selected from the literature as 380 regions most likely specialized in the components of visually guided grasping 381 investigated in our study. We included primary visual cortex, V1, as the first stage of cortical visual processing. Areas LOC, pFS, and PPA within the ventral visual stream 382 (occipitotemporal cortex) were included as they are known to process visual shape 383 and material appearance (Cant and Goodale, 2011; Hiramatsu et al., 2011; Gallivan 384 385 et al., 2014; Goda et al., 2014, 2016), and could thus be involved in estimating object

mass. Areas SPOC, aIPS, PMv, and PMd within the dorsal visual stream 386 (occipitoparietal and premotor cortex) were included as they are thought to transform 387 388 visual estimates of shape and orientation into motor representations (Janssen and Scherberger, 2015). Primary motor and somatosensory area (M1/S1, in the central 389 sulcus) was included as the final stage of cortical sensorimotor processing. The 390 patterns of correlations between model and neural RDMs across participants and 391 392 ROIs (Figure 2B-G) reveal which information was encoded across these visuomotor regions during grasp planning and execution phases. 393

394 Grasp axis encoding in visuomotor regions during grasp planning. Figure 395 2B,C shows that neural representations in V1 and ventral region LOC were 396 significantly correlated with grasp axis during both grasp planning and execution phases. In contrast, representations in ventral areas pFS and PPA were never 397 significantly correlated with grasp axis. Further, grasp axis was significantly 398 399 correlated with neural representations across all dorsal areas (SPOC, aIPS, PMv, PMD), as well as M1/S1, but only during grasp planning. Dorsal and motor areas 400 thus robustly encoded the orientation of the hand when preparing to grasp objects. 401 402 suggesting that the hand-wrist axis was among the first components of the action 403 computed across these regions.

Grasp size was encoded across both visual streams during grasp planning and execution. During the planning phase (Figure 2D), grasp size significantly correlated with neural representations in all ventral areas (LOC, pFS, PPA), and with representations in dorsal regions aIPS and PMd. During the execution phase (Figure 2E), grasp size remained significantly correlated with neural representations in ventral areas LOC and PPA, but not pFS. In the dorsal stream during the execution phase, grasp size remained significantly correlated with neural

representations in PMd but not aIPS, and became significantly correlated with 411 representations in PMv. Neural representations in early visual area V1 were 412 413 significantly correlated with grasp size only in the execution phase, but not during planning. Thus, different ventral and dorsal areas encoded grasp size at different 414 time points. These data suggest that ventral regions may have been initially involved 415 in computing grasp size and might have relayed this information (e.g., through aIPS) 416 417 to the premotor regions tasked with generating the motor codes to adjust the distance between fingertips during the execution phase. It is perhaps surprising to 418 note that neural representations in M1/S1 were never significantly correlated with 419 grasp size, given the well-established role of these regions in sensorimotor 420 processing and motor control. These patterns may align however with findings from 421 422 (Monaco et al., 2015), which suggest that M1/S1 are insensitive to object size, and 423 could be related to work by Smeets and Brenner (Smeets and Brenner, 1999, 2001; 424 Smeets et al., 2019), who propose that grip formation emerges from independently controlling the movements of the digits, rather than the size of the grip aperture. 425

Object mass was encoded across dorsal and ventral streams and in motor 426 427 areas, but only during grasp execution. During the planning phase (Figure 2F), 428 none of the investigated ROIs exhibited any activity that was significantly correlated with object mass. Conversely, during the execution phase (Figure 2G), object mass 429 significantly correlated with representations in ventral areas pFS and PPA, dorsal 430 431 areas aIPS and PMd, and sensorimotor area M1/S1. Object mass was thus encoded in the later stages of grasping. One possible interpretation is that this occurred when 432 433 the hand was approaching the object and was preparing to apply appropriate forces at the fingertips. Alternatively, it could be due to sensory feedback about slippage 434 435 once the object was lifted.

Representational similarities within the grasp network. We took the RDMs generated for each of the nine ROIs (Figure 2) and correlated them with one another to reveal inter-ROI similarity relationships. Figure 3 summarizes the resulting second-order similarity relationships, both within and between planning and execution phases.

We find that neural representations were significantly correlated across many 441 selected ROIs during both grasp planning (Figure 3A) and execution (Figure 3C). 442 Of particular note is that during the planning phase, dorsal regions tended to 443 444 correlate more strongly with one another, while during the execution phase, ventral regions showed more correlated representations. This is revealed by visualising the 445 446 inter-ROI similarities arranged topographically within a schematic brain (Figure 3B 447 and 3D), with the darkness of connecting lines between ROIs proportional to the correlations between their corresponding RDMs. 448

During planning (Figure 3B), the strongest correlations were between M1/S1, PMd 449 450 and aIPS; between V1 and SPOC; and to a lesser extent between SPOC and M1/S1. The structure of these representational similarities is shown also in the 451 multidimensional scaling plot, where a gradient of information can be visualized from 452 V1 through dorsal regions SPOC and aIPS towards motor regions PMd and M1/S1. 453 In the execution phase (Figure 3D) the similarities among brain regions formed two 454 main clusters. One cluster of visual regions was formed by V1, SPOC, and LOC. The 455 second cluster comprised aIPS, premotor areas PMv and PMd, and M1/S1. 456 457 Hierarchical clustering, multidimensional scaling, and topographical plots all highlight how these two clusters appeared to share representational content predominantly 458 459 through ventral stream regions pFS and PPA.

Shared representations across planning and execution phases. Neural 460 representation patterns were also partly correlated across grasp planning and 461 462 execution phases (Figure 3E,F). Notably, aIPS representations during the planning phase were significantly correlated with representational patterns in ventral (PPA), 463 dorsal (SPOC, PMd), and sensorimotor (M1/S1) regions during the execution phase. 464 This suggests that aIPS may play a key role in linking grasp planning to execution. 465 466 Further, neural representation patterns in nearly all ROIs (except PMv) during the planning phase were correlated with representations in V1 during the execution 467 phase, and representations in PFs, SPOC, PMd, and M1/S1 during action planning 468 were correlated with LOC representations during action execution. We speculate that 469 this might reflect mental simulation, prediction, and feedback mechanisms at play 470 471 (see Discussion).

472 Grasp comfort. We recently demonstrated that humans can visually assess which 473 grasp is best among competing options and can refine these judgements by executing competing grasps (Maiello et al., 2021). These visual predictions and 474 haptic evaluations of grasp comfort were well captured by our multi-factorial model 475 476 (Klein, Maiello et al., 2020), suggesting they may play a role in grasp selection. We 477 thus wondered whether we could identify, within the grasp network investigated here, brain regions that encoded visual predictions and haptic evaluations of grasp 478 479 comfort. To this end, once an imaging session was completed, we asked participants 480 (while still lying in the scanner) to execute once more each of the nine grasps and rate how comfortable each felt on a scale of 1 to 10. Comfort ratings were consistent 481 482 across participants (Figure 4A). Comfort was slightly modulated by grasp axis (Figure 4B, t(20)=3.3, p=.0037) and was not modulated by grasp size (Figure 4C, 483 t(20)=0.89, p=.39). The factor that most affected grasp comfort was object mass, 484

with heavy objects being consistently rated as less comfortable than light objects (**Figure 4D**, t(20)=8.1, p<.001). This was also evident when we computed RDMs from comfort ratings (**Figure 4E**) and found that these were significantly correlated with the model RDM for object mass (p<.001) but not with RDMs for grasp axis (p=.54) or grasp size (p=.83) (**Figure 4F**).

Neural representations of grasp comfort were present during both grasp 490 planning and execution phases. To identify brain regions that encoded grasp 491 492 comfort, we next correlated neural RDMs with the average RDM derived from 493 participant comfort ratings. Neural representations in premotor regions PMv and PMd were significantly correlated with grasp comfort during grasp planning (Figure 494 495 **4G**). During the execution phase instead, grasp comfort correlated with neural representations in ventral stream region PPA (Figure 4H). This suggests that dorsal 496 premotor regions encoded the visually predicted comfort of planned grasps (which in 497 our conditions was primarily related to the object mass). Area PPA instead encoded 498 comfort during the execution phase, and might thus be involved in the haptic 499 evaluation of grasp comfort, or some other representation of material properties that 500 501 correlate with comfort.

### 503 **Discussion**

504 Our results show that different regions within the two visual streams represent 505 distinct determinants of grasping, including grasp axis, grasp size, and object mass; 506 moreover, the coding of these attributes differed between grasp planning and 507 execution. Most regions represented multiple factors at different stages. For 508 example, aIPS activity correlated with both grasp axis and size during planning, and with object mass during execution. We found that grasp axis, which is adjusted at the 509 very beginning of reach-to-grasp movements (Cuijpers et al., 2004), was 510 predominantly encoded across dorsal regions during planning. Grasp size, which is 511 adjusted throughout reach-to-grasp movements (Cuijpers et al., 2004), was encoded 512 in different sets of ventral and dorsal regions during grasp planning and execution. 513 Object mass, which gains relevance when applying forces at the fingertips upon 514 hand-object contact (Johansson and Westling, 1988; Johansson and Flanagan, 515 516 2009), was instead encoded across ventral, dorsal and motor regions during grasp 517 execution.

518

### 519 Shift from dorsal- to ventral-stream regions between planning and execution

In the broadest terms, our analyses revealed an overall shift—in terms of representational similarity—from dorsal sensory and motor regions during the planning phase (**Figure 3AB**) to more ventral regions during execution (**Figure 3CD**). During planning, the most similar representations were between V1 and SPOC, SPOC and M1/S1, and between M1/S1, PMd and aIPS, tracing an arc along the dorsal stream to frontal motor areas. SPOC is associated with representations of grasp axis (Monaco et al, 2011), as is parieto-occipital area V6A in the macaque,

which together with V6 is thought to be the macaque homologue of human SPOC 527 (Fattori et al., 2004, 2009, 2010; Pitzalis et al., 2013). The SPOC complex serves as 528 529 a key node in the dorsal visual stream involved in the early stages of reach to grasp movements (Rizzolatti and Matelli, 2003). It is thus interesting to speculate that our 530 findings likely represent the progressive transformation of grasp-relevant sensory 531 representations of an object into explicit motor plans along the dorsal processing 532 533 hierarchy. In contrast, along the ventral stream, individual ROIs (V1, LOC, PPA, pFS) shared similar representations with dorsal sensorimotor areas (particularly 534 aIPS, M1/S1 and PMd), but only weak or no correlation with one another (or with 535 PMv). During planning there was no visual movement to drive common responses 536 537 and it seems reasonable to assume that different ROIs extracted distinct aspects of 538 the stimulus, leading to these rather weak correlations.

During action execution, the picture changed dramatically. Representations in the 539 540 dorsal stream became more independent from one another. Notably, the high similarity between SPOC representations and the more frontal motor regions 541 (M1/S1, aIPS, PMd and PMv) almost disappeared, to be replaced with a stronger 542 correlation with ventral shape-perception area LOC. At the same time, 543 544 representational correlations between ventral visual regions V1, LOC, PPA and pFS, as well as their correlations with PMv increased. This may partly be due to the 545 salient visual consequences of the participant's own actions providing a common 546 547 source of variance across regions. It is interesting to speculate that the overall shift from similar dorsal to similar ventral representations reflects a shift-from the 548 extraction of action relevant visual information during planning-to monitoring object 549 properties to assess the need for corrections during action execution. 550

551 One of the more striking findings from representational similarity analysis (**Figure** 552 **3E,F**) is that activity in V1 during execution correlated with representations in a slew 553 of high visual and sensorimotor areas during the planning phase (this is visible as 554 the column of dark values below V1 in **Figure 3E**, and as the large and dense 555 pattern of connections towards V1 in the Sankey plot in **Figure 3F**).

We speculate that the shift in representations between planning and execution might 556 reflect a role of mental simulation in grasp planning and subsequent comparison to 557 the sensory evidence during execution. During the planning phase, participants may 558 559 be utilizing visual information to compute and compare forward models of potential grip choices (Wolpert and Flanagan, 2001; Cisek and Kalaska, 2010), and possibly 560 mentally simulating potential grasps (Jeannerod, 1995; Jeannerod and Decety, 561 562 1995). These simulations could be used to generate motor plans and sensory predictions. Sensory predictions could then be compared to visual, tactile, and 563 564 proprioceptive inputs during the grasping phase, to facilitate online movement corrections and evaluate the success of the generated motor plan (Desmurget and 565 Grafton, 2000; Wolpert and Ghahramani, 2000; Wolpert et al., 2011). This possibility 566 is supported by recent work showing that planned actions can be decoded from 567 activity in V1 and LOC before movement onset (Gallivan et al., 2013a, 2019; 568 Gutteling et al., 2015; Monaco et al., 2020), and that V1 and LOC are re-recruited 569 when performing delayed actions toward remembered objects (Singhal et al., 2013). 570

571

### 572 Effects of grasp comfort

Grasp comfort was moderately correlated with object mass ( $r \sim 0.3$ ) but not grasp axis nor grasp size, suggesting that other factors also affected comfort (perhaps

even more so than usual because of the movement constraints in the scanner). 575 Grasp comfort was significantly correlated with PPA activation during execution, 576 577 perhaps related to a role for PPA in also coding object mass during execution. More interestingly, activation patterns in premotor cortex (PMv and PMd) were correlated 578 with grasp comfort during planning, even though no regions significantly represented 579 object mass during planning. These results corroborate earlier results implicating 580 581 premotor cortex in grip selection based on orientation (Martin et al., 2011; Wood et al., 2017) and extend the findings to a broader range of factors and to multivariate 582 representations. 583

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### 585 Limitations and future directions

One notable finding of our study is that object mass is encoded in sensorimotor 586 regions during action execution. This is understandable, as information about object 587 mass is required to modulate grip and lift forces. However, we have previously 588 demonstrated that mass and mass distribution also play an important role in 589 590 selecting where to grasp an object (Klein, Maiello et al., 2020). It is thus reasonable to expect processing of object material and mass also during planning, which we did 591 not observe. However, in our study, grasps were preselected. As a result, 592 participants did not need to process an object's material properties to select 593 594 appropriate grasp locations. In order to investigate the role of visual material representations in grasp selection, future research could use our computational 595 framework (Klein, Maiello et al., 2020; Maiello et al., 2021) to identify objects that 596 597 produce distinct grasp patterns, rather than constraining participants to predefined 598 grasp locations. Conditions that require visual processing of object material properties to select appropriate grasp locations would then reveal whether the same 599

or different sensorimotor regions process object mass during grasp planning and
 execution. However, such designs would require disentangling activity related to
 representing shape *per se* from activity related to grasp selection and execution.

603 One factor which is known to be important for grasp selection and execution is grip torque, i.e., the tendency of an object to rotate under gravity when grasped away 604 from its centre of mass (Goodale et al., 1994; Lederman and Wing, 2003; Eastough 605 and Edwards, 2006; Lukos et al., 2007; Paulun et al., 2016). While torque is directly 606 607 related to object mass, it is possible to select different grasps on the same object 608 which produce substantially different torques (Maiello et al., 2021). Since grasps with 609 high torque require greater forces at the fingertips to maintain an object level, humans tend to avoid such high-torque grasps (Klein, Maiello et al., 2020). We 610 611 originally designed our stimuli in the hope of dissociating torque from object mass. Unfortunately, in pilot testing we observed that certain object and grip configurations 612 613 in the magnetic field of the MRI scanner produced eddy currents in the brass portions of our stimuli. These currents caused unexpected magnetic forces to act on 614 the stimuli, which in turn altered fingertip forces required to grasp and manipulate the 615 objects. To avoid the occurrence of such eddy currents in our experiment, we 616 617 decided to forgo conditions differentiating the effects of object mass from those of grip torques. By employing nonconductive materials, in future work our approach 618 could be extended to test whether grasp-relevant torque computations occur in the 619 620 same visuomotor regions responsible for estimating object material and shape. While previous studies have investigated material and shape largely independently, 621 622 one intriguing question for future research is how material and shape are combined 623 to assess the distribution of materials and the consequences of mass distribution on 624 torque and grip selection.

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### 628 Conclusions

Taken together, our results extend previous behavioral and modelling findings about 629 how participants select optimal grasps based on myriad constraints (Klein, Maiello et 630 al., 2020) to reveal the neural underpinnings of this process. Results show that 631 distinct factors - grip orientation, grip size, and object mass - are each represented 632 differently. Moreover, these representations change between grasp planning and 633 execution. Representations during planning rely relatively more heavily on the dorsal 634 visual stream, while those during execution rely relatively more heavily on the ventral 635 636 visual stream. Though surprising, this transition can be explained by a transition from grip selection during planning to monitoring of sensory feedback during grasping 637 execution. 638

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### 855 Figure and Table Legends

Table 1. Regions of interest and their peak x-, y-, and z-coordinates in MNI
space. Search terms used on neurosynth.org with the number of studies the metaanalyses were based on and the extraction date (when the files were downloaded).
V1-coordinates were taken from (Wang et al., 2015).

ROIs in the left hemisphere		Centre		Search term ( <i>neurosynth</i> )	Based on # of studies	Extraction date
			z			
V1 (primary visual)	(Wang et al., 2015)					
LOC (lateral occipital cortex)	-42	-78	-6	lateral occipital	226	July 17 2020
<b>pFS</b> (posterior fusiform sulcus)	-36	-45	-18	objects	692	May 14 2020
PPA (parahippocampal place area)	-30	-45	-9	place	189	Feb. 18 2021
SPOC (superior parietal occipital cortex)	-18	-78	39	reaching	99	June 25 2019
aIPS (anterior intraparietal area)	-42	-33	45	grasping	90	June 25 2019
PMv (ventral premotor)	-56	7	31	grasping	90	June 25 2019
PMd (dorsal premotor)	-24	-12	60	grasping	90	June 25 2019
M1/S1 (primary sensory/motor)	-33	-27	63	grasping	90	June 25 2019

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Figure 1. Study design. (A) Participants in the MRI scanner were cued to grasp 3D 861 objects at specific locations marked by coloured stickers. (B) Sequence of events for 862 863 one example trial during which participants were instructed to grasp the object at the predefined location marked by different colour dots or arrows. Trials began by 864 illuminating the workspace. Through earphones, participants heard the "plan" 865 866 instruction, followed by an auditory cue ("blue", "green", or "red") specifying which grasp to execute based on the coloured stickers marking grasp locations on the 867 868 objects. This initiated the planning phase of the trial. After a jittered delay interval (6-12 s), participants heard the "lift" command, instructing them to perform the required 869 870 grasp. This initiated the execution phase of the trial, in which participants had 7 s to

execute the grasp and return their hand to the start position. Vision of the workspace 871 was then extinguished, and participants waited for the following trial to begin. (C) 872 873 Preselected grasps on stimulus objects of wood and brass produced nine distinct conditions designed to differentiate three components of grasping using RSA. (D-F) 874 RDMs for grasp axis, grasp size, and object mass. Coloured cells represent 875 condition pairs with zero dissimilarity, white cells represent maximum dissimilarity. 876 877 (G) An example RDM computed from fMRI BOLD activity patterns in region PMv of one participant during the planning phase. Note the strong similarity to the grasp axis 878 879 RDM in panel D. (H) Visualization of the selected ROIs within the Colin27 template brain. All ROIs except V1 were built as spheres centred on coordinates recovered 880 881 from neurosynth.org. V1 coordinates were taken from the (Wang et al., 2015) atlas. 882 Note that surface-rendering is for presentation purposes only as data were analysed 883 in volumetric space and no cortex-based alignment was performed.

884

885 Figure 2. RSA results. (A) Mean neural RDMs computed in the nine ROIs included in the study. For visualization purposes only, RDMs within each region are first 886 averaged across participants and then normalized to the full range of the LUT. (B-G) 887 Correlations between model and neural RDMs in each brain ROI during planning 888 (top, B,D,F) and execution phases (bottom, C,E,G). In bar graphs, grey shaded 889 890 regions represent the noise ceiling for each ROI. Bars are means, error bars represent 95% bootstrapped confidence intervals. The same data are represented 891 892 topographically as dots scaled proportionally to the mean correlation in each region. Bright colours represent significant positive correlations (p<.05 with FDR correction); 893 894 correlations shown in dark colours are not statistically significant.

Figure 3. The representational structure of grasping. (A) Matrix showing 896 correlations of data RDMs between regions during the planning phase. White 897 898 asterisks represent significant correlations (p<.05 with Bonferroni correction). (B) The same data in A are shown through hierarchical clustering and 2D 899 multidimensional scaling, and significant correlations are shown topographically. 900 (C,D) As in A, except for the planning phase. (E) Correlations between ROIs across 901 902 planning and execution phases. (F) Sankey diagram depicting significant correlations from E. 903

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905 Figure 4. Grasp comfort. (A) Average grasp comfort ratings for each grasp condition in the fMRI experiment. (B,C,D) Grasp comfort ratings averaged across (B) 906 grasp axis, (C) grasp size, and (D) object mass. (E) Average RDM computed from 907 908 participant comfort ratings. (F) Correlations between grasp comfort and model RDMs. (G,H) Correlations between grasp comfort and neural RDMs in each brain 909 910 ROI during planning (top, G) and execution phases (bottom, H). In bar graphs, grey shaded regions represent the noise ceiling for each ROI. Bright blue bars represent 911 significant positive correlations (p<.05 with FDR correction); correlations shown in 912 dark blue are not statistically significant. The same data are represented 913 topographically as dots scaled proportionally to the mean correlation in each region. 914 Across figure panels, bars are means, error bars represent 95% bootstrapped 915 confidence intervals. \*\*p<0.01, \*\*\*p<0.001 916





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