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Perceptual decisions are biased by the cost to act

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Abstract:

Perceptual decisions are classically thought to depend mainly on the stimulus characteristics, probability and associated reward. However, in many cases, the motor response is considered to be a neutral output channel that only reflects the upstream decision. Contrary to this view, we show that perceptual decisions can be recursively influenced by the physical resistance applied to the response. When participants reported the direction of the visual motion by left or right manual reaching movement with different resistances, their reports were biased towards the direction associated with less effortful option. Repeated exposure to such resistance on hand during perceptual judgments also biased subsequent judgments using voice, indicating that effector dependent motor costs not only biases the report at the stage of motor response, but changed how the sensory inputs are transformed into decisions. This demonstrates that the cost to act can influence our decisions beyond the context of the specific action.

Impact statement: Response action in perceptual decisions is not merely reflecting the upstream decisions, but can recursively influence the decisions about the input sensory stimulus.

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Abstract (150/150)

23 Perceptual decisions are classically thought to depend mainly on the stimulus characteristics, 24 probability and associated reward. However, in many cases, the motor response is considered 25 to be a neutral output channel that only reflects the upstream decision. Contrary to this view, 26 we show that perceptual decisions can be recursively influenced by the physical resistance 27 applied to the response. When participants reported the direction of the visual motion by left 28 or right manual reaching movement with different resistances, their reports were biased 29 towards the direction associated with less effortful option. Repeated exposure to such 30 resistance on hand during perceptual judgments also biased subsequent judgements using 31 voice, indicating that effector dependent motor costs not only biases the report at the stage of 32 motor response, but changed how the sensory inputs are transformed into decisions. This 33 demonstrates that the cost to act can influence our decisions beyond the context of the 34 specific action.

Introduction

38 In laboratory experiments, participants are often asked to make decisions that are purely 39 based on the features of the sensory input -a process that we refer to here as perceptual 40 decision-making. However, in many of our daily situations, decisions are made in a 41 behavioural context, in which the action that follow our decisions can differ dramatically in 42 terms of required physical effort (or the *motor cost*). For example, in the orchard, one may 43 aim to pick the reddest-looking apple from the tree. Some of the apples may be hanging high-44 up on the tree, which will require more effort to pick compared to other fruits hanging on the 45 lower branch. In such situations, does the difference in the motor cost between the options 46 influence the decision of which fruit to pick? If so, is such influence a result of serial 47 integration between the perceptual decision (i.e. decision based on the visual feature) and the 48 motor decision (i.e. decision for action selection to avoid the effortful action) at the output 49 stage, or is the perceptual decision itself is affected by the cost on the downstream action? It 50 has been shown that physical effort is used in motor planning [1-2], and the physical effort to 51 obtain a reward can influence behavioural decisions [3-4]. Moreover, the uncertainty in 52 perceptual decisions is transmitted to the motor system, influencing the parameters of action 53 control [5]. However, it remains unclear whether the motor cost is simply integrated with the 54 perceptual decision to optimise the expected utility [6-7], or whether the preceding 55 experience of unequal motor costs can recursively influence the perceptual decision itself. 56 Here, we show that manipulating the motor response cost for arm movements during a visual 57 motion discrimination task changes not only the decision when responding with the arm, but 58 also when reporting the perceptual decisions verbally.

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Results

64 First, in Experiment 1, we examined if the decision of the visual motion direction can be 65 biased when one of the two responses requires more effort. Ten right-handed participants 66 observed a moving random-dot stimulus and made decisions about the direction of motion 67 (leftward or rightward) [8]. Participants held two robotic manipulanda, one in each hand. 68 They indicated their decision by either moving their left hand (indicating leftward decision) 69 or right hand (rightward decision, Figure 1A). In the baseline phase, the resistance for 70 moving the manipulanda was the same for both hands (velocity dependent resistance: 0.10 71 Ns/cm). In the subsequent induction phase, the resistance for the left hand increased by a 72 small amount each time the participant moved the left hand (0.0008 Ns/cm; Figure 1B). 73 Because the change was gradual, most of the participants did not report becoming aware of 74 the increased motor cost when asked afterwards, even though their left hand was eventually 75 exposed to 1.8 times greater resistance than the right (0.18 Ns/cm for left, 0.10 Ns/cm for 76 right; see Methods and Figure 1- figure supplement). This procedure was employed to 77 minimise any cognitive strategy participants may use, such as explicitly avoiding the costly 78 hand response regardless of the decision about the visual stimulus. In the test phase, 79 participant then continued to perform the visual discrimination task under the accumulated 80 asymmetry in manual resistance. We plotted the proportion of rightward judgment against 81 different stimulus intensities, and determined the point of subjective equality (PSE, the point 82 at which participants judge 50% of the trials to go rightward) for both the baseline and the 83 test phase (Figure 1D). If the increased physical resistance for expressing leftward judgments 84 was incorporated into the decision, the proportion of 'leftward' judgements should decrease 85 in the test phase compared to the baseline, resulting in the shift of PSE towards the left 86 (Figure 1D). As expected, the PSE shifted towards the left from baseline to test phase (-

4.33%, paired t-test (2-tailed): $t_9=2.43$, p=0.038, d=0.76, 8/10 individuals showed the effect) (Figure 1D-E, Figure 1-source data). This indicates that the participants started to avoid making motion direction decisions in which the response is costly.

90 In Experiment 2, we examined whether motor cost and visual features need to be 91 directly associated, or whether simply gaining experience of one action being more effortful 92 than the other is sufficient to bias subsequent decisions. The baseline and the test phase 93 involved judging direction of visual dot motion, as in Experiment 1. However, the induction 94 phase was now replaced with a simple reaching movement, in which the participants moved 95 their left or right hand according to a simple leftward or rightward arrow presented in the 96 centre of the screen. As in Experiment 1, the resistance for moving the left hand was 97 gradually increased. The motor cost during the induction phase was not associated with any 98 motion direction judgement; the participants were only exposed to the gradually increasing 99 motor cost differences between the two hands. Again, PSE significantly shifted leftwards in 100 the test phase (Figure 1E, Figure 1-source data; baseline vs. test; mean -4.26%, paired t-test 101 (2-tailed); $t_8=3.91$, p=0.005, d=1.3, 8/9 individuals showed the effect). This indicates that the 102 direct association of higher motor cost with a specific decision during the induction phase is 103 not critical for inducing the bias. This may suggest that the (implicit) knowledge about the 104 response costs is sufficient to recursively influence the decision. Alternatively, these results 105 could indicate that the bias is only transiently induced during the test phase itself.

In Experiment 1 & 2, we showed that manual motor costs reliably bias decisions that involve these manual response. Where in the process of translating a stimulus into a response does this bias arise? A simple model posits that decision-making occurs in three sequential stages [9]. First, features of the sensory input are extracted and encoded as a sensory representation. Second, a categorical decision is made based on this sensory representation (decision layer). Third, the output from the decision layer is transmitted to the relevant 112 effector for the response (Figure 2). One possibility is that the motor cost only biases the 113 decision layer in the context of the specific response [10] (Figure 2A). In other words, the 114 motor cost only influences decisions when the participant anticipates to perform the action 115 associated with the motor cost, thus, the decision simply takes into account the upcoming 116 motor costs. Alternatively, the repeated exposure to the manual motor cost may affect the 117 perceptual decision about this type of stimulus in general, no matter which effector is used to 118 make a response (Figure 2B) [11-12]. Finally, the motor cost could also directly bias the 119 sensory representation (Figure 2C), affecting the initial encoding of the information before it 120 is transmitted to the decision layer. Only in the two latter scenarios, should the bias observed 121 during the manual decisions generalise to decisions expressed with a different effector. In 122 Experiment 3 we therefore examined whether a hand-specific motor cost could also influence 123 a visual judgement that used a vocal response. A manual to vocal transfer of the motor cost 124 effect would indicate that the motor cost influences the decision about the visual stimulus 125 itself (i.e. perceptual decision), not the decision coupled with the effector selection (i.e. motor 126 decision).

127 Fourteen new participants performed the visual motion discrimination as in 128 Experiment 1. In the induction phase, we gradually increased the resistance for one of the 129 hands while participants performed manual decisions as in Experiment 1. The resistance was 130 increased for half of the participants (7) on the left hand, and for the other half on the right 131 hand, accounting for any hand-dependent effects. To analyse these left and right resistance 132 increase data together, we aligned the data depending on the side of the resistance applied by 133 assigning negative motion coherence level to the motion direction associated with the 134 direction of the resistance. During the manual task participants moved their left or right hand 135 according to their perceived motion direction. For the vocal task, participants indicated the 136 direction of the motion by vocally responding "left" or "right" (Figure 3- figure supplement A) without moving their hands. During the baseline and the test phase, participants alternated between tasks: each 10 trials of manual judgments were followed by 10 trials of vocal judgements (Figure 1C). This "top-up" procedure is commonly used to assess the effect of sensory adaptation on the subsequent perceptual judgements [13]. If the bias induced by the motor cost is affecting the decision regardless of the response effector, the vocal decision should be also biased towards the same direction as the manual decision.

143 For the manual task, the result of Experiment 1 was replicated. The exposure to the 144 resistance made the PSE to shift significantly away from the stimulus associated with the 145 costlier movement (baseline vs. test, mean: -7.06%, paired t-test: t_{13} =2.94, p=0.012, d=0.78, 146 12/14 individuals showed the effect) (Figure 1E, Figure 1-source data). More importantly, for 147 the vocal task, judgement also shifted to the same direction as the manual task (baseline vs. 148 test, mean: -3.00%, paired t-test: $t_{13}=2.44$, p=0.030, d=0.65, 12/14 individuals showed the 149 effect) (Figure 1E, Figure 1-source data), even though the motor cost for the vocal responses 150 was not manipulated. Since the direction of manual motor cost was counterbalanced across 151 participants, this finding cannot be explained by any time-dependent drift of the decision 152 towards one of the directions. This result suggests that the bias induced by the manual motor 153 cost transfers to decisions expressed with other effectors.

154 Although in Experiment 3 the response effector differed between the manual and the 155 vocal task, the abstract response code ("left"/ "right") remained the same between the two 156 tasks. Therefore, it is possible that the manual motor cost got associated with these semantic 157 labels, but did not necessarily influence the stimulus-based perceptual decision itself. To test 158 this possibility, in Experiment 4, we again examined the manual-to-vocal transfer of effect 159 caused by the motor cost, but this time varied not only the response effector, but also the 160 response codes between the two tasks. Twelve new participants performed visual motion 161 judgements, where in the baseline and the test phase, manual decisions and the vocal 162 decisions alternated in a mini-block of 11 and 7 trials, respectively (Figure 3A). The 163 induction phase involved only the manual task, with gradually increasing left hand resistance. 164 As in Experiment 3, the manual task was a left-right motion *discrimination* task. The vocal 165 task, however, was changed to the motion detection task. Participants were asked to detect a 166 near threshold coherent motion by vocally responding "yes" or "no". The to-be-detected 167 motion direction (left or right) was instructed at random before each trial (Figure 3- figure 168 supplement B). Half of the trials included left or right coherent motion, and in the other half, 169 the coherent motion was absent (0% coherence).

170 For the manual task, a significant shift of PSE was observed again, reflecting the 171 avoidance of the costly decision (baseline vs. test, mean: -4.39%, paired t-test : t_{11} =2.88, 172 p=0.015, d=0.75, 9/12 individuals showed the effect) (Figure 1E, Figure 1-source data). For 173 the vocal task, participants' judgement criterion for leftward motion detection became more 174 conservative after being exposed to the manual motor cost, which was not the case for the 175 rightward motion. The interaction between the phase of the experiment (baseline/test) and the visual motion direction (left/right) was significant, $F_{1,11}$ =6.76, p=0.025, η^2 =0.36) (Figure 3B, 176 177 Figure 3-source data). Since the manual task required a left-right decision and the vocal task 178 a yes-no decision, the abstract response code of these two task were different. Therefore, 179 significant manual-to-vocal transfer cannot be simply explained by the motor cost inducing a 180 bias for choosing a particular type of abstract response label. Instead, the results indicate that 181 the motor cost influenced the perceptual decision -i.e. the decision based on the feature of 182 the visual stimulus input - itself.

Together, these results demonstrate that the motor cost on the downstream response can recursively change how the input visual stimulus is transformed into the decision; at the level of sensory representation or at the decision layer. In contrast to the criterion, the sensitivity (d') for the motion detection did not change for either visual motion direction 187 ($F_{1,11}=0.44$, p=0.52, $\eta^2=0.04$) (Figure 3- figure supplement C). This indicates that the motor 188 cost did not increase or decrease the signal to noise ratio (gain) of the motion signal to one 189 specific direction.

190 Until now, we have shown that the motor cost can bias the decision based on a visual 191 stimulus independent from the response effector or abstract response code. Finally, using a 192 model-based approach, we tried to elucidate the processing stage in which the motor cost 193 could have influenced the decision. We analysed both reaction time and choice data of the 194 manual tasks (Experiment 1, 2, 3 & 4; n=45) under the framework of diffusion decision 195 model (DDM) [14]. The DDM postulates that a decision variable temporally accumulates 196 sensory evidence in favor of one decision (by increasing its value) or in favor of the 197 alternative decision (by decreasing its value). When the decision variable hits a certain 198 threshold level (decision bound), the decision is made and the response is triggered [14-15] 199 (Figure 4- figure supplement A). Under this framework, we examined whether the source of 200 the manual decision bias that transferred to the vocal decisions occurred in the sensory 201 representation of the stimulus that is accumulated (Figure 2C; sensory representation) or in 202 the decision bound that is used to make the decision (Figure 2B; decision layer) [14-16].

203 If the bias is introduced at the sensory representation stage, it would increase the input 204 signal (the perceived motion coherence) in the easier direction. We exclude the possibility 205 that the motor cost made the sensory representation of the preferred direction more accurate 206 (increased gain of the signal only in one direction) as we did not observe the discrimination 207 sensitivity change (JND: just noticeable difference) between the baseline and the test 208 condition across different experiments ($t_{44}=0.26$, p=0.77). Rather assumed that the motor cost 209 would shift evidence accumulation towards the easier direction (sensory evidence model; 210 Figure 4- figure supplement 1 B). With this bias, the decision variable would drift towards the 211 preferred decision even in the absence of any coherent visual motion.

212 Alternatively, we considered the possibility that the motor cost changed the decision 213 bounds (decision layer), i.e., the amount of evidence required for each of the choices. This 214 change can be parsimoniously modelled as shift of the starting point of the accumulation 215 process, which will consequently change the distance from the starting point to each decision 216 bound (starting point model; Figure 4- figure supplement 1C). The sensory evidence and 217 starting point models predict qualitatively similar pattern of choice probabilities (i.e. bias 218 towards the direction to avoid the motor cost), but different pattern of decision times for 219 correct trials across different motion intensities (Methods, Figure 4- figure supplement1 B-C). 220 Therefore, by comparing whether which of the two models explains our data better [16-17] 221 (see Materials & Method), we may infer the source of the bias.

222 Additionally to the starting point model and the sensory evidence model, we also 223 fitted a model that allowed for both shifts simultaneously (full model). This allows us to 224 directly compare the effect of each parameter. Also, to check whether the starting point or the 225 sensory evidence shift was necessary to explain the data in the first place, we also prepared a 226 baseline model which we did not model the starting point and/or the evidence accumulation 227 shift, but only modelled the difference in non-decision time (baseline model: see Material & 228 Methods). Note that, since we did not record the reaction time of the vocal decisions, this 229 analysis was restricted to model the bias during the manual decisions.

First, we fit each model to the average group data and compared the BIC weights by converting the Bayesian Information Criterion (BIC) for each model [18]. We then repeated this process 10,000 times, each time drawing 45 participants from our sample with replacement to obtain an estimate of the reliability of our conclusion. The results (Figure 4C-D, Figure 4-source data, Table 1) clearly indicate that the starting point model explained the data substantially better than the other models. Second, we compared the model parameter of the full model fitted to each participants' individual data. Consistent with superior fit of the starting point model, we found a significant shift of the starting point (median; 5.6%, signed rank test : $z_{44}=2.50$, p=0.01, d=0.32; Figure 4A, Figure 4-source data), but no significant change in the evidence accumulation (median; 1.38%, signed rank test : $z_{44}=1.15$, p=0.25, d=0.21; Figure 4B, Figure 4-source data). Therefore, our data suggests that the motor cost biased the decisions by changing the decision layer (starting point) that transforms the input signal into the decision.

243 The DDM also contains a parameter that captures the motor response time that is 244 independent from the decision (non-decision time; see Material & Methods). In the baseline 245 phase, there was no significant difference between the non-decision time of the hands 246 $(462.8 \text{ ms vs. } 468.8 \text{ ms, paired t-test :} t_{44}=0.94, p=0.34, d=0.08)$. However, in the test phase, 247 although the non-decision time became shorter for both the hands without resistance (dTA: -248 7.69ms) and the hand with resistance (dTB: -27.7ms), the decrease was larger for the hand 249 with resistance (paired t-test : $t_{44}=2.69$, p=0.01, d=0.64). This finding resembles a previous 250 report [17], which demonstrated that the stimulation of the caudate neuron with visual motion 251 directional tuning biased monkey's motion direction judgments towards the neuron's tuned 252 direction, but at the same time decreased the estimated non-decision time for the response 253 (eye movement) to the opposite (non-stimulated) direction.

While the DDM models were only fit to the choice probabilities (psychometric function) and the RT function of the *correct* trials (chronometric function, see Material & Methods), we also checked whether the models could predict the patterns of RTs on error trials. For this purpose, we simulated individual trials using the estimated group parameters based on the starting point and the sensory evidence models (Table 2). For the correct trials, both model simulations showed similar tendencies; the RT reduced for the non-costly motion stimulus compared to the costly stimulus (Figure 4- figure supplement2 A-B left panel). The 261 pattern of the error trial RT differed between the two simulations. For the starting point 262 model, error RTs were *shorter* for the costly motions (non-costly decision), whereas the 263 pattern was opposite for the sensory evidence model (Figure 4- figure supplement2 A,B). 264 This is because, for the former, the distance between the starting point and the non-costly 265 decision bound decreases, whereas for the latter, the drift rate increases towards the error 266 decision direction for the costly stimulus (i.e. non-costly decision) [19]. The pattern of RTs 267 for the experimental data (Figure 4- figure supplement2 C) was qualitatively similar to that of 268 the starting point model. Therefore, the general pattern of error RTs supported our claim that 269 the motor cost induced a starting point shift.

270 We showed that participants incorporate the cost of the response into the perceptual 271 decision, and flexibly changes the way of interpreting the sensory environment. To further 272 investigate the temporal dynamics of these flexible changes, we examined how the induced 273 bias developed over the course of the 10 (Experiment 3) or 7 (Experiment 4) trials of vocal 274 decisions following a series of manual decision trials (see detail in the Methods). In 275 Experiment 3, on average, PSE shift was slightly stronger for the vocal trials that 276 immediately followed the manual task (mean shift of PSE; -3.51% for the first 5 trials (initial 277 point of Figure 3C), >-3% for the rest, Figure 3-source data), although this time dependence 278 did not reach significance ($F_{5, 65}=0.60$, p=0.75). In Experiment 4, the strength of bias 279 (criterion shift) significantly decayed depending on the number of trials from the manual task, 280 showing a stronger bias in the first 4 out of 7 trials (initial 2 time points of the curve. Figure 3D, Figure 3-source data, $F_{4,44}=2.70$ p=0.042, $\eta^2=0.2$). These results indicate that the 281 282 biasing effect may be relatively short-lived. However, the time scale of the retention is 283 comparable to common perceptual adaptations, such as motion aftereffects. Mather et al. [20] 284 shows that on maximum, the motion aftereffect lasts for 10~15 seconds. A single trial of our 285 task takes at least, 3~4 seconds, so our effect lasted for 9~16 seconds. Therefore, our results

- indicate that, in the absence of any further confirmatory evidence of asymmetric response
 costs for the decision, the brain readapts relatively quickly to the new situation, resembling
 other examples of spontaneous decay in perceptual and motor adaptation phenomena [20-22].
 This shows that while perceptual decisions can be updated relatively quickly and flexibly,
 they do exhibit a substantial memory of past motor costs.

Discussion

In this study, we showed that visual motion direction decisions can be biased by the cost of the action that is used to report the decision (the *motor cost*). Moreover, we demonstrated that the motor cost indeed affects the decision about the input stimulus identity, and not only the decision about which action to select.

299 Previous behavioural studies have shown that the perceptual decisions can be biased 300 by changing the frequency (expectation) of stimulus presentation, or by manipulating the 301 response-reward association for the correct/incorrect decisions [19, 23]. Here we demonstrate 302 that motor costs associated with the response can also bias the perceptual decisions, even 303 when the response is made with a completely different effector that is not associated with 304 increased motor cost (here, verbal instead of manual responses). Therefore, our study 305 provides evidence that the cost on the response for perceptual decisions, which has been 306 regarded as downstream output channel of the decision, can recursively influence the 307 decision of the input stimulus itself. In other words, the observed bias not only reflects the 308 serial integration of the transient motor cost into the ongoing decision [6], but represents a 309 more global change in the way of transforming the sensory input to the decision, by taking 310 the prior experience of the motor cost into account [24].

Congruent with our results, a recent study has shown that asymmetric biomechanical costs induces a bias into the decisions, and that this bias cannot be explained by strategically choosing the easier option when perceptual uncertainty is high [25]. The critical contribution of our study is to show that this influence on the decision process is not limited to the judgments involving the asymmetric motor cost, but generalized to judgment using vocal responses without motor cost manipulation. The present study parsimoniously shows that the motor cost influence is not simply due to the bias of decision at the motor

318 preparation/execution stage.

319 Our DDM analysis readily explains the effect of motor cost as the change in the 320 required amount of input evidence (i.e. shifts of the starting point) for the decision. Even 321 though only fitted to the reaction times for correct trials [15], this model also correctly 322 predicted the RT pattern for error trials. These findings are consistent with previous literature 323 that shows that increasing the presentation frequency or amount of reward for one of the 324 choice biases decision in a way that can be best modelled as a starting point shift [19]. Indeed, 325 it has been suggested that shifting the starting point of accumulation process is the optimal 326 solution to account for such contextual changes [26-27]. It should be noted, however, that 327 alternative models involving collapsing bounds may perform better in situations in which the 328 stimulus strength varies randomly [28-29, but also see 30].

329 Electrophysiological studies have shown that the electrical stimulation of parietal or 330 basal ganglia neurons can bias perceptual decisions [16-17]. These effects were explained by 331 shifts of the starting point in the DDM framework (or equivalently the decision bounds), thus 332 the change in the decision layer of the perceptual task. Therefore, these brain regions are 333 likely candidate neuronal substrates where the motor cost interacts with the sensory input to 334 bias the perceptual decision. Neurons in the lateral intraparietal area (LIP) code the feature 335 that is relevant for the visual decision, independent of response type [11]. Experiment 3 & 4 336 similarly suggested motor-induced changes for the perceptual decision is independent of the 337 effector used for response. The subcortical network in the basal ganglia has been suggested 338 to represent the cost of action or the "vigour" of movement initiation [31]. Prolonged 339 exposure to altered motor costs during perceptual decisions may similarly change the 340 response properties of these areas, altering how the system judges the sensory evidence from 341 the environment.

342 How does our current finding relate to the existing theories of perceptual decision 343 making? One of the recent theories is the intentional framework [32]. This framework posits 344 that decisions and actions are tightly coupled, with each decision maker separately 345 accumulating the sensory evidence until the threshold level for the specific action is reached. 346 In this scenario, any decision bias induced by imposing a motor cost to a specific action 347 would not transfer to a decision performed by a different action, as there is no explicit 348 communication between the multiple decision makers. Thus, our results indicate that 349 perceptual decisions are either made centrally by a high-order process that is common across 350 different actions [12, 33], or at least that different local decision makers exhibit a certain 351 degree of mutual dependency, such as a shared cost (value) of the input stimuli (external 352 environment).

In conclusion, we demonstrate that the motor cost involved in responding to a visual classification task is integrated into the perceptual decision process. Our everyday perceptual decisions *seem* to be solely based on the incoming sensory input. They may be, however, influenced by the preceding history of physical cost of responding to such input. The cost of our own actions, learned through the life-long experience of interacting with the environment, may partly define how we make perceptual decisions of our surroundings.

Material & Methods

361 *Participants*

362 A total of 52 participants (Experiment 1: 12 (6 females), Experiment 2: 10 (5 females), 363 Experiment 3: 16 (8 females), Experiment 4: 14 (5 females); with ages ranging from 18 to 38 364 years (M=25.5) participated in the study. All had normal or corrected-to-normal vision, were 365 right-handed and naive regarding the experimental purpose. None of them declared any 366 history of neurological diseases. All participants gave informed written consent, and all 367 procedures were approved by the UCL ethics committee. No statistical test was run to 368 determine sample size a priori. The chosen sample sizes are similar to those in previous 369 publications related to perceptual decisions [34-35]. Furthermore, we replicated the result of 370 Experiment 1 in the subsequent Experiment 2, 3 & 4 using the similar sample sizes.

371

372 General Apparatus

373 Participants were seated comfortably in front of a virtual environment setup, which has been 374 described in more detail previously [36]. The visual stimulus was presented on the display, 375 which was mounted 7 cm above the mirror. The mirror was mounted horizontally above the 376 manipulanda, preventing direct vision of the hands but allowed participants to view a visual 377 scene on the monitor. During the task, participants leaned slightly forward with their 378 forehead supported by a forehead rest, maintaining the distance from the eye and the mirror 379 constant (25 cm). As a result, the viewing distance from the eye to the monitor was 32 cm. 380 The chair was placed at the position where the participants could most comfortably perform 381 the reaching movement using the manipulanda. Depending on the judgement of the visual 382 stimulus (see below), they made 15 cm straight reaching movements while holding onto a 383 robotic manipulandum (update rate 1 kHz, recording of position and force data at 200 Hz) using their left or right hand (Figure 1A). The hand positions were represented by white circles (cursors, 0.3 cm diameter) located vertically above the real positions of the hands. The movement were executed from a starting box (unfilled white squares, 0.5 cm size, 6 cm to the left and right from body midline) to a target box (unfilled white squares, 1 cm size).

388

389 Visual motion stimulus

In the centre of the screen, random-dot motion stimulus was presented [8] (Figure 1A). In a 9 deg diameter circular aperture, dots were presented in a density of 1.7 dot/deg². The speed of the dots was 10 deg/sec. For each trial, 0%, 3.2%, 6.4%, 12.8%, 25.6%, or 51.2% of the dots moved coherently to the left or the right. All other dots moved in a random direction, picked for each dot separately between 0 and 360 deg.

395

396 Experiment 1

397 Task and the movement practice

398 The trial started with the participants moving the two cursors into the starting boxes. After a 399 delay of 800ms, a random-dot stimulus was presented. Participants were instructed to judge 400 the direction of the visual motion (left or right), and to make a ballistic reaching movement to 401 the target with either hand. The left judgement required left hand movement, and the right 402 judgement required right hand movement. Initiation of the hand movement made the dot-403 motion stimulus disappear [37]. The stimulus also disappeared if no response had been made 404 after 750ms from the stimulus presentation. Participants were asked to start moving (make 405 their decisions) as quickly as possible, but before the stimulus disappeared. After the 406 movement, the hands were automatically pushed back near to the starting boxes.

407 To maintain stable movement kinematics throughout the experiment participants 408 underwent three different types of practice sessions before the main experiment. First,

409 participants responded to a series of 100% coherent leftward or rightward dot motion trials. 410 Participants were asked to perform their reaching movement with a peak velocity of >40 cm/s, 411 and land the cursor within 1.5 cm from the target. When a trial fulfilled this criterion, the 412 visual target "exploded", informing the participants about the success of the movement. Each 413 training block consist of 48 trials, and the participants continued this training until their 414 success rate exceeded 65% within a block. Next, participants performed three blocks of the 415 same task but using the graded coherence levels as used in the main experiment (66 trials 416 each). Participants were particularly instructed to initiate the response before the stimulus 417 disappeared. Feedback information about the movement kinematics was also presented (see 418 above). Participants were clearly informed that the feedback was not about whether the 419 motion direction judgement was correct or incorrect, but about whether their motor 420 performance matched the requirements. Finally, participants performed three blocks of the 421 same task without movement feedback. Participants who could not perform the movements 422 according to the speed criterion did not proceed to the main experiment (2 participants).

423

424 Structure of the experiment and the resistance control

There were three phases in the main task; the baseline phase, induction phase and the test phase. Participants performed the same motion direction judgment throughout the experiment, but the resistive force they were exposed during each of the hand movement was different between the phases.

- Each phase consisted of 5, 15, 5 blocks of trials, respectively. Each block contained 66 trials, and each the 11 movement direction x coherence level combinations was repeated 6 times in each block.
- 432 The resistive force (f) was velocity dependent, calculated as from the equation;
- $\mathbf{f}_{\mathbf{x}\mathbf{i}}\mathbf{f}_{\mathbf{y}} = -\alpha [\mathbf{v}_{\mathbf{x}\mathbf{i}}\mathbf{v}_{\mathbf{y}}]$
 - 19

434 where *v* denotes for the movement velocity, and α denotes for the coefficient of the viscosity 435 (Ncm/s). Here, negative value indicates the force against the movement direction.

In the baseline phase, the coefficient was set to 0.10 Ns/cm for movements of either hand. In the induction phase, the resistance increased by 0.0008 Ns/cm for each left hand movement. The strength increased until the coefficient reached 0.18 (Ns/cm), and this value remained for the rest of the induction phase and the test phase (Figure 1B; upper panel). Progression of the actual peak value of the resistive force (N) through the experiment is presented in Figure 1- figure supplement.

442 Our aim of gradually increasing the resistance force was to make the resistance 443 implicit as possible to the participants, avoiding any cognitive strategy to be involved when 444 performing the task. After the experiment we assessed their awareness using three questions. 445 We first asked participants whether they had realised any change in the task during the 446 experiment", and then more explicitly "whether they had realized that the resistance 447 increased for either of the hand". Only the participants clearly stating "no" to both of the 448 questions were included in the analysis. Two participants who clearly realised the increased 449 left hand resistance (answer "yes" to both of the questions) were excluded from the analysis. 450 The same procedure was adopted for the remaining experiments; 1, 2, and 2 participants were 451 excluded from the analysis of Experiment 2-4, respectively.

452

453 Analysis

Movement onset was defined as the point when the movement velocity exceeded 2.5 cm/s. Reaction time was defined as the time elapsed between the onset of the visual stimulus to movement onset. Reaction times smaller than 100ms or larger than 850ms were excluded from the analysis, since the former decision is unlikely to be based on the visual motion, and the latter is likely to be made after the stimulus disappearance. Movement end was defined as

459 movement velocity falling below 2.5 cm/s. If both hands moved, the hand with the larger 460 movement amplitude was taken as the participant's decision (leftward or rightward) on that 461 trial. Probability of detecting a slight movement for the non-judged hand was 1.9% of all of 462 the trials across 4 experiments. When the movement amplitude of each judged and the non-463 judged hand was calculated, in Experiment 1, the average amplitude was 15.4 cm and 3.2 cm 464 respectively. For the movement of the non-judged hand, the movement amplitude that 465 exceeded 2SD from the mean movement amplitude was 5 trials for 1 participant, 1 trial for 2 466 participants and 0 trials for the rest of the participants. We confirmed that excluding these 467 few trials did not affect any of the subsequent analysis performed on this data. Same 468 confirmation was also done for Experiment 2 (judged; 13.93cm, non-judged; 0.23 cm; above 469 2SD: 3 trials for 1 participant, 2 trial for 1 participant, 1 trial for 1 participant), Experiment 3 470 (judged; 15.5cm, non-judged; 2.1 cm; above 2SD: 0 trial for all of the participants) and 471 Experiment 4 (judged; 15.3cm, non-judged; 2.6 cm; above 2SD: 0 trial for all of the 472 participants).

473 For each participant, the percentage of 'right' judgement responses for each visual 474 motion coherence level was calculated. Logistic regression was used to describe the function 475 of participant's response against the motion strength. The point of subjective equality (PSE), 476 i.e. the motion coherence level at which the participant answered "rightward" in 50% of the 477 trials was estimated from each regression. This was done independently for the baseline and 478 the test phase, and the PSEs between the two phases were compared using paired t-test (two-479 tailed). As for all other statistical comparisons, Levene's test was used to confirm the equality 480 of variance before performing this statistical comparison. We additionally confirmed that all 481 of the result from the above parametric tests can be replicated by the non-parametric 482 Wilcoxon's signed rank test, which shows that our data is not biased by the particular 483 statistical test used to assess the results.

485 Experiment 2

The experiment was largely similar to Experiment 1, except that during the induction phase, reaching movements were not associated with any visual motion judgments. Participants were required to make a left or right hand reaching, according to the arrow presented in the centre of the screen, which pointed either to the left or to the right. Otherwise, the procedure was equivalent to Experiment 1.

491

492 Experiment 3

493 The structure of the experiment was similar to Experiment 1 & 2; where baseline phase was 494 followed by an induction phase, and finally with the test phase. In the induction phase, the 495 resistance for one of the hands slowly increased while the participants performed the manual 496 perceptual decision about the dot motion (moving left hand for leftward motion, and right 497 hand for right motion). The resistance increased on the left hand for half of the participants 498 (7) and on the right hand for the other half, aimed to account for any hand- dependent effects. 499 For the dot motion, ten different strength (i.e. coherence level of the motion) were used (\pm 500 3.2%, $\pm 6.4\%$, $\pm 12.8\%$, $\pm 25.6\%$, $\pm 51.2\%$; negative value indicates leftward motion, and the 501 positive for the rightward motion). The induction phase involved 14 blocks of 60 trials each.

502 During the baseline and the test phase, participants alternated between responding to 503 the visual motion manually (manual task) or vocally (vocal task). During the manual task 504 participants moved their left or right hand according to their perceived motion direction. For 505 the vocal task, participants were asked to indicate the direction vocally without moving their 506 hands. The vocal task started with a tone. After 1500ms, a random-dot motion stimulus was 507 presented for 500ms. Participants were asked to judge whether they perceived a motion 508 direction towards the left or to the right, by vocally answering "left" or "right". Their 509 response was recorded by the experimenter.

Each 10 trials of manual judgments were followed by 10 trials of vocal judgements (mini-block; Figure 1C, Figure 3- figure supplement A). Within a mini-block, the manual and the vocal tasks were presented serially, and this structure was repeated four times within a block (in total, 80 trials per block). Participants performed 4 blocks each for the baseline phase and the test phase.

515

516 Analysis

The analysis of the manual task was similar to the above experiments. To analyse left and right resistance increase data together, we aligned the data depending on the side of the resistance applied, by assigning negative motion coherence level to the motion direction associated with the direction of the resistance. This is equivalent to converting the right resistance increase data to the left resistance increase data; which was the case for Experiment 1 & 2. The vocal task was analysed similarly to the manual task, in which the PSE between the baseline and the test phase was compared.

524 To examine the time-dependent effect of the manual motor cost onto the vocal 525 decision, we analysed the vocal task data depending on the number of trials from the last 526 manual trials. To obtain enough trials for the analysis, we calculated the PSE using the first 5 527 trials of a mini-block of 10 vocal trials. This procedure was repeated by shifting the window, resulting in 6 analysis ranges (1st-5th, 2nd-6th, 3rd-7th, 4th-8th, 5th-9th, 6th-10th trials). Finally, 528 529 PSE of the vocal task during the baseline phase was subtracted from these 6 values. These 530 values will indicate the change in the strength of the influence of manual motor cost on the 531 vocal decisions over time. We performed a one-way ANOVA to examine this temporal 532 change.

534

535 Experiment 4

536 The procedure was generally similar to Experiment 3, with the main difference that the vocal 537 task was a motion *detection* task, rather than a motion *discrimination* task as used for the 538 manual task. Also, as in Experiment 1 & 2, the resistance increased for the left hand during 539 the induction phase. The vocal task started with a tone, and the to-be-detected motion 540 direction (left or right) was instructed (Figure 3A, Figure 3- figure supplement B). After 541 1500ms, a random-dot motion stimulus was presented for 500ms. The stimulus included 542 either the near threshold level coherent motion towards the instructed direction or a 0% 543 coherent random-dot motion. Participants were asked to judge whether they perceived a 544 coherent motion towards the instructed direction or not, by vocally answering "yes" or "no". 545 Their response was recorded by the experimenter. The strength of the motion coherence was 546 defined individually before the experiment to approximately match 75% correct rate, causing 547 the percentage correct rate to be between 65% and 85% during the baseline phase of the task.

The aim of the vocal task was to examine whether the bias induced by the motor cost would transfer to the judgment using the different response effector. Additionally, the task was designed such that the abstract response code of the manual task (left-right) would be unrelated that of the verbal task (yes-no). Therefore, the performance of the vocal task could not be biased by the manual task through its commonality of the effector or response code.

553 11 trials of manual task were followed by 7 trials of vocal task (Figure 3A). This 554 combination of manual/vocal task mini-block was repeated for four times in a block. 555 Therefore, the manual and the vocal tasks were performed serially, similar to Experiment 3. 556 Participants performed six blocks, during each of the baseline phase and the test phase. The induction phase was similar to that of Experiment 1, and contained only the manual tasks, 13blocks of 66 trials each.

559

560

561 Analysis

The analysis of manual task was identical to the above experiments. For the vocal task, responses for left motion trials and right motion trials were analysed independently. Any trial in which a hand movement was detected during vocal task was excluded from the analysis. For each motion direction, the sensitivity (d') and the bias (criterion; C) were calculated using signal detection theory [38]. Difference of these measures between the baseline and the test phase were compared between the leftward and the rightward motion using 2-way ANOVA (phase (2) x motion direction (2)).

569 We found that the criterion (C) for the leftward motion became more conservative 570 after exposed to increased resistance on the left hand (Figure 3B). As in Experiment 3, we 571 also examined whether the strength of this effect decayed as a function of the number of trial 572 since the last manual trial. We calculated the d' and C for both leftward and rightward motion 573 using the first three trials of the vocal judgment in each mini-block (3trials x 24 mini-blocks 574 = 72 trials). We repeated this procedure by shifting the window by 1 trial, resulting in the 5 analysis ranges 1st~3rd, 2nd~4th, 3rd~5th, 4th~6th, 5th~7th trial. Then, the values calculated 575 576 similarly for the baseline (d' and C, each for leftward and rightward motions) were subtracted, 577 to calculate the change from the baseline condition. Finally, to test for a difference in bias for 578 left and right motions, the left values were subtracted from the right values [i.e. negative 579 values indicate less sensitive (or more conservative) judgments for leftward motion]. 580 Intuitively, this shows how the leftward or rightward bias of d' and the C changes over time 581 as the temporal (trial) distance increases from the preceding manual judgment trials. We

performed a one-way ANOVA to examine the temporal change of the left-right bias duringthe vocal task.

- 584
- 585

586 Diffusion Decision Model (DDM) analysis

587 Data of the manual judgement task from Experiment 1, 2, 3 & 4 (n=45) were re-analysed 588 together under a framework of Diffusion Decision Model (DDM) [14], to examine the 589 possible source of the decision bias; whether it is 1) increasing the sensory evidence 590 favouring one of the decision (change in the sensory representation; Figure 2C, Figure 4-591 figure supplement B), or 2) shifting the starting point of the evidence accumulation process 592 more near to one of the decision bounds (equivalent to changing distance to each of the 593 decision bounds) (change in the decision layer; Figure 2B, Figure 4- figure supplement C). 594 For this, reaction time and the choice data of both baseline and the test phase was 595 simultaneously modelled with the DDM, and the estimated parameters were evaluated [15-596 17]. Since we did not obtain the reaction time for the vocal trials, only the manual decision 597 trials across different experiments were analysed. We analysed only the data for non-zero 598 motion coherence level (Experiment 3 did not have 0 coherence level condition) and for the 599 RTs for the correct decision trials, which are established to be well explained by the DDM 600 [15,39]. The sign of the data from the participants having resistance on the right hand was 601 flipped (Experiment 3), allowing the data to be analysed together with the left hand resistance 602 increased participants.

For the baseline phase, the model had five basic parameters; *A*, *B*, *k*, *T01* and *T02*. In this framework, momentary motion evidence is drawn randomly from a Gaussian distribution $N(\mu, 1)$, where μ is calculated as a motion strength (coherence level: Coh) scaled by the parameter *k*: $\mu = k \times Coh$. Decision is transformed into action when the accumulated 607 momentary motion evidence reaches either of the decision bound; A (right decision) or -B608 (left decision). Here, leftward decision is the one with the higher resistance for the response. 609 Decision time is defined as the elapsed time between the stimulus onset and the time when 610 the evidence reached either of the decision bound (Figure 4- figure supplement 1 A). Reaction 611 time is the sum of decision time and the non-decision time (*T01* for a left and *T02* for a right 612 judgement), where the non-decision time is a pure action processing time that is assumed not 613 to depend on the amount of the sensory evidence.

614 The expected value of rightward judgments across different coherence levels can be 615 calculated as [15]:

$$\frac{e^{2\mu B}-1}{e^{2\mu B}-e^{-2\mu A}}.$$

617 The average decision time for the rightward motion decision can be described as:

618
$$\frac{A+B}{\mu} \operatorname{coth}(\mu(A+B)) - \frac{B}{\mu} \operatorname{coth}(\mu B),$$

619 , and for the leftward motion decision as:

620
$$\frac{A+B}{\mu} \coth(\mu(A+B)) - \frac{A}{\mu} \coth(\mu A)$$

621 To explain the change in decision bias observed between the baseline and test phase within 622 the same model, additional parameters that describe the change in the parameters across two 623 phases (baseline and test) were added to the above five base parameters (delta parameters). 624 Three different models with different delta parameter settings were generated. In the first 625 model (sensory evidence model), the motor cost changed the sensory evidence by changing 626 the motion coherence by *dcoh*. Thus, the motion strength in the test phase was μ = 627 $k \leq (Coh+dcoh)$. Since we know that the effect of motor cost does not change the 628 discrimination sensitivity (just noticeable difference: JND), but changes only the PSE (Figure 629 3C), change in the sensory evidence is modelled as *addition* to the input stimulus (+dcoh), 630 rather than as the change in the gain itself (direct change of k). In the second model (starting 631 point model), parameter that indicates the shift of the starting point of the accumulation 632 processes (sp) was added, which will consequently change the amount of evidence required 633 for each decision. Equivalently, we can think of this parameter as a shift in the two decision 634 bounds to [A-sp] and [-B-sp], leaving the distance between the two bounds fixed. In the final 635 model (full model), both coherence level change (*dcoh*) and the starting point shift (*sp*) were 636 added as additional parameters.

637 In all models across the three models, we also modelled the difference in the non-638 decision time between the baseline and the test phase. There were 840 (Experiment 3) \sim 990 639 (Experiment 1) trials of reaching movement between the baseline and the test phase, and the 640 reaction time is decreased in the test phase compared to the baseline phase regardless of the motion coherence level (F(1,35)=11.95, p=0.0015, η^2 =0.255). We assume that this was due 641 642 to the reduction of the non-decision time induced by the repetition of the reaching movement. 643 To account for this, we added an additional parameter modelling the decrease of the non-644 decision time across the two hands. Since such reduction of the non-decision time may differ 645 between the left and the right hand, the difference was modelled separately for the right 646 (dTA) and the left (dTB). Therefore, the non-decision time for the test phase was modelled as 647 T01- dTA and T02- dTB for right and left, respectively (same model as ref 17).

As a result, the three DDM models consisted of 8 (sensory evidence model; 5 basic parameters + dTA + dTB + dcoh), 8 (starting point model; 5 basic parameters + dTA + dTB + sv), and 9 (full model; 5 basic parameters + dTA + dTB + sv + dcoh) parameters, respectively. In addition to these three experimental models, we also prepared a baseline model, in which we fit the baseline and the test phase data only with the delta parameter of non-decision times. (7 parameter baseline model; 5 basic parameters + dTA + dTB).

The DDM we used in this study is the most basic one proposed by Palmer et al., [15]. This simple version of the DDM predicts the choice probabilities (psychometric function) 656 and the mean RT function (chronometric function) of the correct trials. Therefore, this model 657 is sufficient to distinguish between the models of interest -a change in starting point of 658 evidence accumulation (Figure 4 – Figure supplement B-C). A number of extensions to the 659 DDM framework have been proposed to explain the full RT distributions of correct and 660 incorrect trials using trial-by-trial variability of the drift rate [14] or by incorporating the 661 time-dependent decision bounds [40]. While these extensions are important, they do not 662 change the primary predictions regarding the mean RT and choice probabilities under the two 663 models. For the sake of parsimony, we therefore use the simpler model here.

664 The group-averaged reaction time and choice data of the experiments was first fitted 665 by each of the four models (three models + baseline model), by searching the parameters that 666 minimized the negative log likelihood of the fit (maximum likelihood estimate). We used the 667 group-average data, as each individual had a limited number of trials, and the noise level was 668 rather high. This can induce a bias towards more complex models, as it can over fit the noise. 669 Using group-average data strongly attenuates this effect [41-42]. To obtain estimates of the 670 reliability of the group-average fit, we resampled the data 10,000 times across participants 671 with replacement, and fit the model to each of the averaged resampled data [43]. To select the 672 best model to explain the data from the above four, the Bayesian Information Criterion (BIC) 673 [44] was calculated for each model,

674

$BIC = -2 \log L + \alpha \log(n),$

where $\log L$ denotes for log likelihood of the fitted function, α for number of parameters used for the fit and *n* for number of data points in the sample. The latter term in the BIC equation penalises the number of parameters used for the fit. Therefore, smallest BIC among the three models will indicate the most parsimonious model. To compare the explanative power between each model in an intuitive way, we converted the BIC values to the BIC (Schwartz) weights [18] which expresses the explanatory power of BIC values into ratios among thecandidate models.

682

683

$$w(i) = \frac{\exp\{-1/2 \triangle BIC(i)\}}{\sum_{k=1}^{K} (\exp\{-1/2 \triangle BIC(k)\})}$$

models used to

explain the data, $\Delta BIC(i)$ is the difference in BIC from the model with the smallest (best) BIC. The descriptive statistics (averaged and the 95% confidence interval of the 10,000 bootstrap) of BIC value and the BIC weight distributions are summarised in Table 1.

We also estimated the delta parameters (*dcoh*, *sp*) of the full model for each individual – thereby avoiding possible biases in the parameter estimates when using averaged data [45]. The parameters were statistically tested against zero (no significant change in the test phase compared with the baseline phase) using a Wilcoxon's signed rank test. The impact of *sp* depends of the distance between the two decision bounds. Therefore, we normalised the individual starting point shift (*sp*) by the estimated distance between the two decision bounds (*sp*/[*A* + *B*]).

694

695 DDM simulation analysis for error trial RTs

where K is the number of

696 The parameters of the DDM models were estimated using the proportion of correct decisions 697 and the RT data for correct trials. To test whether this model could also capture the pattern of 698 error RTs, we simulated single trial data from the starting point and the sensory evidence 699 models (10,000 times for each stimulus strength per condition), using the parameters 700 estimated from the group data (Table 2). In both models, the leftward judgements is costlier 701 in the test phase. For each simulation, the RT difference between the baseline and the test 702 phase for both correct and error trials was calculated, separately for the leftward and 703 rightward motion stimulus. We also calculated the difference in the correct rates. Then we 704 compared these patterns with the actual experimental data analysed in a same way.

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835 Figures & Figure Legends

Table 1					
BIC and BIC weights calculated for different DDM					
		starting point model	sensory evidence model	full model	baseline model
BIC	averaged	346.09	360.37	348.76	432.88
(95% conficence interval)	upper bound	433.94	447.89	441.07	547.49
	lower bound	335.04	348.64	337.62	401.31
BIC weight	averaged	0.7911	0.0006	0.2083	0.0000
(95% conficence interval)	upper bound	0.8600	0.4303	0.7445	0.0000
	lower bound	0.0600	0.0000	0.1336	0.0000

 * BIC and the BIC weights for different DDM models. Values calculated using the group averaged data, and the 95% confidence interval is calculated from the 10,000 bootstrap resampling is presented

Table 2							
Parameter estimates for data							
DDM parameters	k	A	В	T01(dTA)	T02(dTB)	sp	dcoh
starting point model	0.29	11.76	12.02	460 (-9)	459 (-28)	-1.62	0
sensory evidence model	0.29	11.59	12.20	460 (-17)	458 (-22)	0	4.00
* Parameters for the simulat							



875 Figure 1

876 A: Participants made 15cm reaching movement to the target with their hand (left or right), in 877 response to the perceived direction (left or right) of the random-dot motion. B: In all of the 878 experiments, the baseline phase and the test phase was interleaved by the induction phase, in 879 which the resistance for one of the manipulandum movement gradually increased. C: In 880 Experiment 3, the baseline and the test phase included both manual and vocal motion 881 discrimination, each being serially presented within a 10 trial block. D: Fitted psychometric 882 function to the probability of a response towards the right in the baseline (blue) and the test 883 (red) phase of a representative participant (Experiment 1). Negative motion coherence value 884 indicates the leftward motion (with manual resistance), and positive towards the right 885 (without manual resistance). E: Shift of PSE from the baseline in Experiment 1, 2, 3 & 4. 886 Negative value indicates the PSE shift towards the motion direction with resistance (i.e. 887 decreased judgements towards the motion direction having resistance in their manual 888 response). Error bars indicate standard error of mean across participants. Data for Figure 1E 889 is available as Figure 1-source data. *p < 0.05, ** p < 0.01



909 Figure 1- figure supplement

910 Example of the peak resistive force increase profile in the study. The presented data is force 911 data from Experiment 1, averaged across trials and participants in each session. Here, each 912 session contains 66 trials (33 trials for each left and right) of reaching movements. Since the 913 resistive force is provided in a velocity dependent manner, the variance is reflecting the 914 variability of the movement velocity across participants.



946 Figure 2

947 Schematic diagram illustrating the process of perceptual decision making, and the possible 948 influence of the motor cost on the decision process. Perceptual decision making consists of 949 three different processing stages. First, the features of the sensory input are extracted and 950 encoded as in the sensory representation. Second, the perceptual (categorical) decision is 951 made based on this sensory representation (decision layer). Finally, the decision is transferred 952 to the response effector. The motor cost asymmetry during the manual response can affect the 953 perceptual decision making process in several different ways. (A) The motor cost for the 954 manual response may only bias the decision layer that involves this response, but leave the 955 decision layer for different response effectors unaffected. If this is the case, the bias observed 956 during the manual response should not generalize to the verbal response. (B) The motor cost 957 may bias the decision layer in general or (C) the sensory representation directly. In either of 958 the latter two cases, the effect of motor cost should be also observable during the response 959 using the different effector.



963 Figure 3

964 A: In Experiment 4, participants made vocal judgements to a yes-no motion *detection* task, 965 and manual judgement to a left-right *discrimination* task. **B**: Shift of the criterion of motion 966 detection from the baseline during the vocal judgement task in Experiment 4 (d' data is 967 presented in the Figure 3 – Figure Supplement C). Negative value indicates the shift towards 968 more conservative criterion for the motion detection. C: PSE shift from the baseline 969 condition in Experiment 3, plotted against the number of trials from the preceding manual 970 judgements. Negative value indicates the shift of PSE towards the motion direction with resistance (i.e. decreased judgements towards the motion direction having resistance in their 971 972 manual response). D: Vocal motion detection criterion differences between the leftward (with 973 manual response resistance) and rightward (without resistance) motion (Experiment 4). The 974 difference is plotted against the number of trials from the preceding manual judgements. 975 Negative value indicates a more conservative criterion for leftward than for rightward motion. 976 Error bars indicate standard error of mean across participants. Data for Figure 3B-D is 977 available as Figure 3-source data.*p < 0.05



1010 Figure 3- figure supplement

1011 A,B: The task instruction of the vocal task in Experiment 3 (A) and 4 (B), where the 1012 participants were asked to vocally discriminate the motion direction (Experiment 3), or asked 1013 to vocally detect the motion for the instructed direction (Experiment 4). C: Shift of the d-1014 prime (sensitivity) of motion detection from the baseline during the vocal judgement task 1015 (Experiment 4). D: Difference in d' for leftward and rightward motion direction in the vocal judgement of Experiment 4, plotted against the number of trials from the preceding manual 1016 judgements. Positive value indicates the higher sensitivity for the rightward motion and the 1017 1018 negative for the higher sensitivity to the leftward motion. Error bars indicate standard error of 1019 mean across participants. 1020



1049 Figure 4

1050 A,B: Histogram of individual starting point shift (A) and the evidence accumulation shift (B) 1051 calculated from the DDM (full model). Black dotted line indicates the 0% point (i.e. no 1052 effect), and the red dotted line indicates the median of the distribution (i.e. amount of shift). Significant rightward shift of the starting point was observed (median: 5.6%), whereas not for 1053 1054 the evidence accumulation shift (median: 1.39%).C, D; Fit of DDM to the choice (C) and the 1055 decision time (D) data averaged across participants (see Methods and Figure 4- figure 1056 supplement Panel C). Data for Figure 4A-D is available as Figure 4-source data. p < 0.051057



1085 Figure 4- figure supplement 1

1106

1086 Schematic diagram explaining the drift diffusion model (DDM) and the simulated choice and 1087 decision time data. A: DDM model postulates that a decision is transformed into action when 1088 the evidence favouring one of the choices has been accumulated to a certain threshold level 1089 (decision bound) (left panel). The model makes a prediction about the pattern of choice 1090 probability and the decision time in respect to the strength of the motion signal (right panel). 1091 For the baseline, the starting point of the evidence accumulation is set to 0. B: When there is more sensory evidence in favour of rightward motion (red line), the drift speed for the 1092 1093 rightward decision will increase (left panel), and left would decrease. As a result, a rightward 1094 decision becomes more likely (shift of psychometric function) and the decision time pattern 1095 generally shifts to the left, showing a tendency to respond faster for the rightward motion 1096 (right panel). If the motor cost influences the sensory representation (Figure 2C), we would 1097 expect this pattern of results (sensory representation model). C: A shift in the starting value 1098 of the accumulation process induces a prior bias towards a rightward decision, decreasing the 1099 required amount of evidence for rightward decision compared to the left (left panel). This 1100 will again bias the decision to favour the rightward decision. Instead of shifting the pattern of 1101 decision times to the left (as in **B**), the starting point model predicts an additional offset to the 1102 rightward and leftward decision time; shorter for the rightward decision and longer for the 1103 leftward decision. In this model the bias therefore arises from a change in the decision layer 1104 transforming the sensory representation into the decision (Figure 2B), while the sensory 1105 evidence itself is not changing.



1137 Figure 4- figure supplement 2

1138 Change of the correct RT, error RT and the correct rate from the baseline to the test phase. A: 1139 simulated data from the starting point model, **B**: simulated data for the evidence 1140 accumulation model, **C**: actual experimental data (n=45). Left and right indicates the stimulus 1141 motion direction. The left decision was associated with the increased resistance during the 1142 test phase. Simulation parameters are based on the estimated parameters from the actual data 1143 (Table 2). Error bars in **C** indicate standard error of mean across participants.

1145 Legend for the source data

1146 Data that can be used to reconstruct the main figures are provided as source data. Data for each panel 1147 of the figure is separated in different sheets of the excel file, which are named accordingly.

- 1148 **Figure 1-source data**: Individual PSE shift for Experiment 1-4, which is the data summarized in 1149 Figure 1E.
- 1150 Figure 3-source data: Individual criterion shift of the vocal trials (Experiment 4; summarized in
- 1151 Figure 3B), individual PSE shift for the vocal trials across different trials (Experiment 3; summarized

in Figure 3C) and individual criterion shift for the vocal trials across different trials (Experiment 4; summarized in Figure 3D)

1153 summarized in Figure 3D).

Figure 4-source data: Individual starting point shift in the test phase from the baseline phase during the manual trials, estimated from the full-model DDM (summarized in Figure 4A), individual evidence accumulation shift in the test phase from the baseline phase during the manual trials, estimated from the full-model DDM (summarized in Figure 4B), data points consisting the psychometric function estimated from the DDM (starting point model) using the group averaged data (summarized in Figure 4C) and data points consisting the chronometric function estimated from the

1160 DDM (starting point model) using the group averaged data (summarized in Figure 4D).





















