

Task goals shape the relationship between decision and movement speed

Fanny Fievez, Ignasi Cos, Thomas Carsten, Gerard Derosiere, Alexandre

Zénon, Julie Duqué

► To cite this version:

Fanny Fievez, Ignasi Cos, Thomas Carsten, Gerard Derosiere, Alexandre Zénon, et al.. Task goals shape the relationship between decision and movement speed. Journal of Neurophysiology, 2024, 10.1152/jn.00126.2024. hal-04785120

HAL Id: hal-04785120 https://hal.science/hal-04785120v1

Submitted on 15 Nov 2024 $\,$

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers. L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

1	Task goals shape the relationship between decision
2	and movement speed
3 4	Fanny Fievez ¹ *, Ignasi Cos ^{2,3} , Thomas Carsten ¹ , Gerard Derosiere ^{1,4} , Alexandre Zénon ⁵ , Julie Duque ¹
5	
6 7 8 9 10 11 12	 ¹Institute of Neuroscience, Université catholique de Louvain, Brussels, Belgium. ²Facultat de Matemàtiques i Informatica, Universitat de Barcelona, Catalonia, Spain. ³Serra Hunter Fellow Programme, Catalonia, Spain. ⁴Centre de Recherche en Neurosciences de Lyon, France. ⁵Institut de Neurosciences Cognitives et Intégratives d'Aquitaine, Bordeaux, France.
13	
14	
15	
16	
17	
18	
19	* CORRESPONDENCE TO:
20	Fanny Fievez
21	Institute of Neuroscience
22	Université catholique de Louvain
23	53, Avenue Mounier
24	COSY- B1.53.04
25	B-1200 BRUSSELS
26	Belgium
27	Email: fanny.fievez@uclouvain.be
28	Web: http://www.coactionslab.com

30 Abstract

The speed at which we move is linked to the speed at which we decide to make these 31 32 movements. Yet, the principles guiding such relationship remain unclear: while some studies point towards a shared invigoration process boosting decision and movement 33 34 speed jointly, others rather indicate a tradeoff between both levels of control, with slower movements accompanying faster decisions. Here, we aimed (1) at further 35 investigating the existence of a shared invigoration process linking decision and 36 movement and (2) at testing the hypothesis that such a link is masked when 37 detrimental to the reward rate. To this aim, we tested 62 subjects who performed the 38 tokens task in two experiments (separate sessions): Experiment 1 evaluated how 39 changing decision speed affects movement speed while Experiment 2 assessed how 40 changing movement speed affects decision speed. In the latter experiment, subjects 41 were either encouraged to favor decision speed (fast decision group) or decision 42 accuracy (slow decision group). Various mixed model analyses revealed a 43 44 coregulation of decision (urgency) and movement speed in Experiment 1 and in the fast decision group of Experiment 2, but not in the slow decision group despite the fact 45 that these same subjects displayed a coregulation effect in Experiment 1. Altogether, 46 47 our findings support the idea that coregulation occurs as a default mode but that this form of control is diminished or supplanted by a tradeoff relationship, contingent on 48 49 reward rate maximization. Drawing from these behavioral observations, we propose that multiple processes contribute to shaping the speed of decisions and movements. 50

- 51
- 52
- 53
- 54
- 55

57 New & NoteWorhty

The principles guiding the relationship between decision and movement speed are unclear. In the present behavioral study involving two experiments conducted on 62 human subjects, we report findings indicating a relationship that varies as a function of the task goals. Coregulation emerges as a default mode of control that fades when detrimental to the reward rate, possibly due to the influence of other processes that can selectively shape the speed of our decisions and movements.

65	5 key words: Decision making, Urgency, Vigor, Reward Rate, Human
66	
67	
68	
69	
70	
71	
72	
73	
74	
75	
76	

77 Introduction

Every day of our life, we make decisions to interact with our environment in a 78 79 goal-directed manner. Several models have been developed to explain how we select actions by describing decision making as a process of noisy accumulation of evidence: 80 during deliberation, sensory evidence is accumulated until the total evidence in favor 81 82 of one of the potential actions reaches a certain threshold, at which point the decision 83 is made and an action is initiated (Gold & Shadlen, 2007; Hanks et al., 2014; Ratcliff et al., 2016). In the context of motor behavior, such accumulation directly converts into 84 an increase of neural activity in the motor cortex, from a starting point to a consistent 85 decision threshold (Cisek & Thura, 2022; Kelly et al., 2021; Ratcliff & Smith, 2004). In 86 these models, the time taken to select a motor act is a direct function of the speed with 87 which motor activity grows (based on evidence) and of the amount of activity required 88 to reach the threshold, which sets the accuracy criterion. 89

90 Decisions can be made even when evidence is low or absent, suggesting that the accuracy criterion can be reduced if necessary. For instance, if we unexpectedly 91 reach a junction when driving a car, we must rapidly decide whether to turn left or right, 92 93 regardless of readiness and evidence, increasing the risk of an inappropriate choice. Past studies have suggested that this decrease in accuracy criterion can be 94 implemented by an evidence-independent rising "urgency signal" pushing motor 95 activity close to decision threshold, which is mathematically equivalent to a lowering of 96 the latter (Churchland et al., 2008; Cisek et al., 2009; Ditterich, 2006; Murphy et al., 97 2016; O'Connell et al., 2018; Thura, 2020). Computationally, this urgency signal is 98 typically modelled as increasing linearly over time (Cisek et al., 2009; Derosiere et al., 99 2019, 2021, 2022; Kelly et al., 2021) it includes an intercept, which reflects the degree 100 101 to which motor activity is upregulated already at the onset of the decision process (i.e.,

102 context-sensitive effect), and a slope, which reflects how fast motor activity will be 103 pushed towards the decision threshold as time elapses (i.e., time-sensitive effect).

Reward plays an important role in animal behavior and "reward rate" 104 105 maximization is a prominent principle in the field of decision making (Lemon, 1991; Shadmehr et al., 2019). More precisely, the reward rate is the sum of all rewards 106 acquired through our actions, minus the costs implied over the total time spent (Carland 107 et al., 2019; Yoon et al., 2018). Critically, the urgency signal described in models of 108 decision making is typically considered as useful for maximizing the reward rate 109 (Carland et al., 2019; Charnov, 1976; Thura et al., 2012). That is, by its context-110 sensitive effect, the urgency signal can shorten the time invested to obtain the reward. 111 In addition, by its time-sensitive effect, it allows to make decisions without waiting 112 indefinitely, even when there is only little or no evidence. 113

Several observations in both human and non-human primates indicate that the 114 time one takes to decide impacts the speed of the movement implementing the 115 decision (Churchland et al., 2008; Thura et al., 2014; Drugowitsch et al., 2012). That 116 is, faster decisions are typically followed by quicker movements. Interestingly, the 117 reverse relationship has been observed too: one study in our lab has revealed that 118 when the context requires movements to be performed in a shorter time period, the 119 decisions leading to them arise faster, compared to contexts in which subjects have 120 more time to perform the same movement (Carsten et al., 2023). Altogether, these 121 findings suggest that the urgency signal implemented in decision making models may 122 not solely operate at this restricted level but may shape behavior in a global manner, 123 coregulating the speed of both decisions and movements (Carsten et al., 2023; Thura, 124 2020). This "coregulation hypothesis" is consistent with the view that the urgency signal 125 serves to maximize reward rate, as in most situations a speeding up of both decision 126

and movement will shorten the time required to obtain a reward (Shadmehr et al.,
2019). Also consistent with this hypothesis is the fact that some studies have reported
a time-sensitive effect of decision urgency on movement speed: that is, within a given
context, movements that are initiated following a longer deliberation are typically faster
than movements associated with earlier decisions, reflecting well the linear increase in
urgency over time (Thura et al., 2014; Thura, 2020).

The "coregulation hypothesis" has received systematic support from studies 133 investigating the impact of decision urgency on movement speed (Carsten et al., 134 2023; Thura et al., 2014; Thura, 2020). By contrast, studies that have addressed this 135 relationship inversely, by looking at the impact of movement speed on the pattern of 136 decision speed, have reported mixed findings (Carsten et al., 2023; Kita et al., 2023; 137 Reynaud et al., 2020; Saleri Lunazzi et al., 2021). As mentioned above, we recently 138 observed changes in decision speed in relation to context-dependent adjustments in 139 movement speed that are consistent with the coregulation hypothesis (Carsten et al., 140 141 2023). It is interesting to note that in the latter study, the increase in decision speed when subjects had to perform faster movements occurred even when there was no 142 possibility of saving time by doing so; that is, making faster decisions did not allow to 143 shorten the trial/block duration. This led us to think that coregulation of decision and 144 movement may be a ubiquitous feature of human behavior, one that occurs by default 145 even when not required, arising from a neural organization that has developed 146 because most real-life (urgent) situations require rapid actions (i.e., including fast 147 decisions and fast movements). Yet, in their recent work, Thura and his team have 148 149 reported a slowdown of decision speed (rather than a speedup) in contexts requiring subjects to perform faster movements (Reynaud et al., 2020; Saleri Lunazzi et al., 150 2021), reminiscent of a tradeoff rather than a coregulation effect. Yet importantly, this 151

bunch of work used an experimental design in which subjects knew that a block would
only end after a fixed number of correct decisions. Hence, here speeding up decisions
was detrimental to the reward rate, as the gain of time on a trial basis would have led
to lengthening the experiment, given the decline in accuracy that typically accompanies
faster decisions.

Based on these collective findings, it appears that if an urgency mechanism exists in 157 the brain, it must interact with other processes that provide human beings with a flexible 158 control of decision and movement for adaptive behavior according to the task goals, 159 as previously suggested (Saleri Lunazzi et al., 2021) but never tested directly. Here, 160 we addressed this idea in two behavioral experiments on healthy young human 161 participants who performed a variant of the Tokens task in different contexts. 162 Specifically, we tested the prediction that decision and movement durations would be 163 linked by default in this task but that this coregulation would disappear in the same 164 subjects when detrimental in terms of reward rate, as a function of the context in which 165 they perform the task. 166

167 Methods

168 **Participants and ethical statement**

169 A total of 62 healthy human volunteers were recruited for this study, but due to technical issues the data were processed on 56 subjects (30 women, 24.6 ± 3.4 years 170 old). All participants were right-handed according to the Edinburgh Questionnaire 171 172 (Oldfield, 1971) and had normal or corrected-to-normal vision. None of them had any neurological disorder or history of psychiatric illness or drug or alcohol abuse; and no 173 one was following any clinical treatment that could have influenced performance. The 174 175 protocol was approved by the Ethics Committee of the Université catholique de Louvain (UCLouvain), Brussels, Belgium (approval number: 2018/22MAI/219) and 176

adhered to the principles expressed in the Declaration of Helsinki. Participants werefinancially compensated for their participation and provided written informed consent.

179 Setup and task

Experiments were conducted in a quiet and dimly lit room. Participants were seated in 180 front of a 21-inches cathode ray tube computer screen, placed at 60 cm from the 181 participant's eyes and used to display stimuli during the task. The display was gamma-182 corrected, and its refresh rate was set at 75 Hz. Participants' forearms were positioned 183 in a neutral position (i.e., at 0 degree of pronation and supination) on a Canadian board, 184 185 used to standardize and fix the resting position of the index fingers with elastic bands. Moreover, two lasers (targeting the tip of each index finger) were used to indicate the 186 resting position (i.e., 0 degree of index flexion) and the minimum amplitude of the left 187 or right index finger movement required in the task (i.e., 30 degrees of flexion, see Fig. 188 1.A and below for more details). 189

We used a variant of the Tokens task (Cisek et al., 2009;Thura et al., 2014) which has already been exploited in various ways in several past studies of our lab (Derosiere et al., 2019, 2022; Fievez et al., 2022) The current version of the task was implemented with Matlab 2016 (The Mathworks, Natick, Massachusetts, USA) and the Cogent 2000 toolbox (Functional Imaging Laboratory, Laboratory of Neurobiology and Institute of Cognitive Neuroscience at the Welcome Department of Imaging Neuroscience, London, UK).



197

Figure 1. Experimental material A. Setup. Participant forearms were positioned in a neutral 198 position on a Canadian board, with elastic bands maintaining the index fingers in a resting 199 position. Two lasers (targeting the tip of each index finger) were used to indicate the resting 200 201 position (i.e., 0 degree of flexion; laser 1) and the minimum amplitude (i.e., 30 degrees of flexion; laser 2) of the left or right index finger movement required in the task. B. Task. Each 202 trial starts with an initiation phase during which participants have to perform a bilateral flexion 203 204 of index fingers to signal their readiness. When index fingers return to their resting position, the 3 circles remain empty for a variable pre-decision period (150-300 ms). Then, 15 tokens 205 appear in the central circle and start jumping one by one every 200 ms. Subjects are required 206 207 to determine, as soon as they feel ready, which lateral circle will end up with the largest number of tokens (left one in this example), and to report their decision with a left or right index finger 208 209 movement triggering a pacman animation (more details can be found in the main text). Once the movement phase is over, the central circle finishes to empty with the final token jumps. 210 The trial ends with a feedback (fully successful trial in this example; more in the main text) 211 followed by a blank screen of variable intertrial duration (1800-2000 ms). 212

213

214 Sequence of events in a trial

The overall sequence of events for each trial of our task is depicted in Figure 1.B. Each trial starts with the appearance of 3 empty blue circles (4 cm diameter each), placed on a horizontal axis, with the sentence "Ready to start" displayed below them. During this initiation phase, subjects are required to perform a bilateral flexion of index fingers to indicate that they are ready to start the trial. When index fingers return to their resting position, the 3 circles remain empty for a short pre-decision phase of random duration

(150-300 ms). The decision phase then starts with the appearance of 15 randomly 221 arranged tokens (0.3 cm diameter) in the central circle that start to jump one by one 222 from the center to one of the 2 lateral circles, every 200 ms. The task of the subjects 223 is to determine which of the two lateral circles will end up with the largest number of 224 tokens and to report their decision with a left or right index finger movement. The 225 movement phase involves a pacman animation that will be described below in more 226 details. Once this phase is over, the final tokens continue to jump until the central circle 227 is empty (i.e., until the 15th token jump; Jump₋₁₅). Note that subjects are told that they 228 are expected to respond before Jump-15, as soon as they feel sufficiently confident. 229 230 The trial always ends with a feedback (see below for more details) which is followed by a blank screen during a variable intertrial interval (1800-2000 ms). 231

232 Trial types and success probability

The difficulty of the decision in each trial of the task depends on the dispersion of 233 234 tokens along the jumps, which could point more or less obviously to one of the lateral circles. This pattern of token distribution and the degree to which it affects success of 235 the subjects can be formalized with what is called the "success probability". That is, for 236 each trial *i*, and at each moment in time, we can define the success probability $p_i(t)$ 237 associated with choosing a response (left or right). If at a moment, the left (L) circle 238 contains NL tokens, the right (R) once contains NR tokens, and NC tokens remain in 239 the central (C) circle, then the probability that the left response is ultimately the correct 240 one (i.e., the success probability of guessing left) is described as follows: 241

242
$$p(L|NL, NR, NC) = \frac{NC!}{2^{NC}} \sum_{k=0}^{\min(NC, 7-NR)} \frac{1}{k! (NC-k)!}$$
(1)

Calculating this quantity for the 15 token jumps allowed us to characterize the temporal 243 profile of success probability $p_i(t)$ for each trial. As such, as far as the participants knew, 244 the individual token jumps and the correct choice were completely random. However, 245 we interspersed distinct trial types within the full sequence of trials. First, in 60% of 246 trials, the $p_i(t)$ remained between 0.33 and 0.66 up to Jump₋₈, that is, the initial token 247 jumps were balanced between the lateral circles, keeping the $p_i(t)$ close to 0.5 until late 248 in these "ambiguous" trials. As such, in ambiguous trials, the tokens jumped 249 alternatively to the correct and incorrect lateral circles until Jump-8, such that the 250 number of tokens was equal in both lateral circles after each even jump (i.e., after 2, 251 252 4, 6 and 8 jumps) and a difference of one token was present after each odd jump (i.e., after 1,3,5 and 7 jumps). Second, in 20% of trials, the $p_i(t)$ was above 0.7 after Jump-3 253 and above 0.8 after Jump₅, that is, the initial jumps consistently favored the correct 254 choice in these "obvious" trials. In the remaining 20% of trials, the $p_i(t)$ was below 0.4 255 after Jump₋₃, that is, the initial jumps favored the incorrect choice and the following 256 ones favored the correct choice in these "misleading" trials. 257

258 Sensory evidence and SumLogLR

As in previous studies (Cisek et al., 2009; David Thura et al., 2014; Derosiere et al., 2022), we assumed that participants would estimate the level of evidence based on the number of tokens that have already jumped into the two side circles rather than by calculating the probability of success. This estimation can be computed as a first-order approximation of the real probability function after each jump (see Eq. 1), called the sum of log-likelihood ratios (SumLogLR):

265
$$SumLogLR(n) = \sum_{j=1}^{n} log \frac{p(e_j|C)}{p(e_j|U)}$$
(2)

In this equation, $p(e_i | C)$ is the likelihood of a token event e_i (a token favoring either the chosen or the unchosen response) during trials in which the chosen response C is correct, and $p(e_i | U)$ is the likelihood of e_i during trials in which the unchosen response U is correct. The SumLogLR is proportional to the difference between the number of tokens that favored each of the 2 possible choices (i.e., that moved toward each lateral circle) at any given time.

272 Index finger movement and pacman animation

273 As explained in more detail below in the "Experimental design" section, testing our predictions required us to characterize and/or to manipulate the movement features of 274 index finger responses. To allow us to do so, we asked the subjects to provide their 275 276 response, not with a single finger movement as we usually do, but with a tapping movement involving a repetition of 4 index finger flexions, with the left or right hand 277 depending on their decision in the Tokens task. Moreover, this tapping movement was 278 associated with a pacman animation. That is, as soon as the first tap was completed 279 (i.e., flexion of at least 30 degrees, as indicated by the laser device), a pacman 280 appeared together with 3 additional tokens in front of it, on a horizontal axis, as shown 281 on Figure 1.B. Subjects knew that each further tap would allow the pacman to "eat" 282 one of these supplementary tokens. The pacman was presented together with a ghost 283 which will be described in the "Experimental Design" section, as its features depended 284 on the experimental condition the subjects were in. Notably, the pacman animation 285 often ended with a blank screen to cover the minimum 3000 ms period of the 286 movement phase: as such, completing the tapping movement faster never allowed to 287 shorten the trial duration, as in Carsten et al, 2023. Finally, note also that trials in which 288 subjects did not provide a response before Jump-15 did not involve any pacman 289

animation; in this case participants had instead to remain still in front of a blank screen

for a period corresponding to the movement phase duration.

292 Trial feedback and score calculation

As a feedback at the end of the trial, the chosen circle turned either green or red, 293 depending on whether the choice was correct or incorrect, respectively. The feedback 294 also included a numerical score presented below the central circle, which depended 295 on both the decision and movement requirements of the task. Subjects got +5 points 296 for a correct decision and another +5 points for a correct tapping movement (see below 297 for specific movement requirements). Hence, fully successful trials were worth +10 298 299 points (i.e., +5+5), as illustrated on Figure 1.B. Then, any failure, whether at the level 300 of the decision or the movement, was penalized by -2 points. Hence, a partially successful trial was worth +3 points (i.e., +5-2 or -2+5), while a fully failed trial led to -301 4 points (i.e., -2-2). Finally, in the absence of response before Jump-15 (i.e., a no-302 response trial), the displayed score corresponded to 0 point and came along with a 303 'Time Out" message at the bottom of the screen. All trial scores were summed up and 304 displayed at the end of each block, providing a global feedback on the block to maintain 305 motivation of participants. 306

307 Experimental Design

Participants performed two experiments as part of the current study. These experiments occurred on separate days (average interval of 9 ± 8 days) and in a counterbalanced order. In Experiment 1, we designed the task such that, in separate blocks, subjects were either encouraged to make slow or fast decisions. The purpose here was to further investigate the existence of a shared invigoration process linking decision and movement by looking at how contextual changes in decision speed would influence movement speed. Inversely, in Experiment 2, we aimed at testing the reverse

relationship, thus how contextual changes to movement speed (slow or fast) influence 315 decision speed. In addition, to test the hypothesis that such a link is masked when 316 detrimental to the reward rate, we separated subjects in two groups who performed 317 the slow and fast movement blocks in a context that either favored fast (fast decision 318 group) or slow decisions (slow decision group). As such, we predicted that fast 319 movement blocks would involve faster decisions (as compared to slow movement 320 blocks) in the fast decision group (where coregulation is beneficial) but not in the slow 321 decision group (where coregulation is detrimental). The specific features of these two 322 experiments are described in the sections below. 323

324 Experiment 1

All subjects (n=56) took part in Experiment 1. This experiment required participants to 325 326 perform the Tokens task in two different block types, where a small adjustment to one trial event (the final jumps phase) allowed us to promote either slow (accurate) or fast 327 decisions (see Fig. 2.A). That is, in the "slow decision" blocks, tokens kept on jumping 328 every 200 ms during the final jump phase, as in the decision phase, until the central 329 circle was empty. In contrast, in the "fast decision" blocks, final tokens jumped much 330 331 faster (i.e., every 50 ms), such that deciding faster allowed subjects to finish the trial 332 earlier. Because blocks had a fixed duration of 265 sec, deciding earlier in fast decision 333 blocks allowed subjects to perform more trials and thus to accumulate more points. This was not the case in the slow decision blocks, where it was a better strategy to 334 decide later and reach a higher accuracy, given the fixed number of trials (26) that they 335 would be able to do over the same block duration (always about 265 sec). All of this 336 was made explicit to the subjects to enhance the change in decision policy between 337 the two block types. Finally, as mentioned above, the pacman animation during the 338 movement phase also involved a ghost which, in this experiment, always chased the 339

pacman at a fixed speed established during pilot tests. Subjects knew that they had to 340 avoid the ghost and would get a negative feedback (-2 points, as explained in the 341 feedback section above) if they tapped so slowly that they got caught, in which case 342 the pacman turned into a skull. Yet this happened very rarely because the imposed 343 speed was easy to attain, as it was just there to exhort subjects to do their tapping 344 movement in a row, as opposed to encourage them to go as fast as possible. That is, 345 subjects were able to escape the ghost on most trials, regardless of the block type (see 346 Fig. S1 in supplementary materials). 347



348

Figure 2. Protocol of Experiment 1. A. Task. In this experiment, participants performed two
 block types that differed according to the speed at which the final tokens jumped in the lateral
 circles at the end of the trial (after the finger tapping movement). That is, fast final jumps (every
 50 ms) led participants to prioritize decision speed (fast decision blocks) while slow jumps
 (every 200 ms) led subjects to rather prioritize decision accuracy (slow decision blocks). B.
 Manipulation check. Participants adjusted their decision policy depending on the type of block

by making faster (shorter decision duration) and less accurate (lower %Correct) decisions in
 fast (blue bars) relative to slow (white bars) decision blocks. Error bars represent SE. ***p <
 0.001.

358

359 Experiment 2

All subjects also performed Experiment 2 but due to a lack of data after cleaning, 2 360 subjects had to be excluded from the analysis (n=54; 32 Women, 24.5 ± 3.3 years old). 361 As shown on Figure 3.A, in this experiment again there were two different block types, 362 which here differed according to the movement speed requirement. That is, subjects 363 were explicitly asked to report their decision in the Tokens task with a tapping 364 movement that was either fast, in the "fast movement" blocks, or slow, in the "slow 365 movement" blocks. The exact speed that subjects had to adopt in both block types 366 depended on their spontaneous speed. In the fast movement blocks, subjects had to 367 tap at a speed that was twice the spontaneous speed (± 20%), while the speed in the 368 slow movement blocks had to be equal to the spontaneous speed or to any value below 369 370 it. The spontaneous tapping speed was calculated during a calibration phase at the beginning of the experiment, by asking subjects to perform a block of 15 trials of the 371 Tokens task in a neutral condition, with no specific instruction regarding decision or 372 movement speed. Once the average spontaneous speed was determined based on 373 these trials, the participants were then specifically trained to perform fast tapping 374 movements at the required speed (i.e., twice the spontaneous speed) during 4 blocks 375 for each index finger. In these blocks, subjects repetitively tapped their index finger 376 and each of these movements was followed by a feedback indicating if the tapping was 377 "ok", "too fast" (>20% above the targeted speed) or "too slow" (<20% below the 378 targeted speed). A block ended as soon as subjects had completed 9 tapping 379

- 380 movements at the targeted speed. There was no training for the speed of slow
- movement blocks as this speed was the one obtained spontaneously.



382

Figure 3. Protocol of Experiment 2. A. Task. In this experiment, participants performed two 383 block types that differed according to the speed at which they had to perform the finger tapping 384 movement; that is, at twice the spontaneous speed (fast movement blocks: pacman chased 385 386 by ghost) or at about the spontaneous speed (slow movement blocks; pacman preceded by ghost). Moreover, subjects were split into two experimental groups according to whether they 387 performed the version of the task that led them to prioritize decision speed due to fast (every 388 50 ms) final jumps (fast decision group, upper panel), or to prioritize decision accuracy due to 389 slow (every 200 ms) final jumps (slow decision group, lower panel). B. Manipulation check. 390 As required by the instruction in this Experiment, participants displayed shorter (faster) tapping 391 movements in the fast (red bar) than slow (white bar) movement blocks, regardless of whether 392 393 they belong to the fast or slow decision group. Error bars represent SE. ***p < 0.001.

As in Experiment 1, tapping movements in the Tokens task were performed in relation 395 to a pacman (and ghost) animation, where each tap provided the opportunity to "eat" 396 an additional token placed on a horizontal axis. Yet, here the animation served the 397 further purpose to control for the movement speed instruction in each block type. First, 398 to provide a guide to subjects, the ghost here was either moving behind the pacman, 399 chasing it, in the fast movement blocks, while it was preceding the pacman, in the slow 400 movement blocks (see Fig. 3.A). Given the continuous requirement to avoid a collision 401 with the ghost, this feature reminded the subjects to tap rapidly (to escape the ghost) 402 in the fast movement blocks and incited them to tap tranquilly (to avoid bumping into 403 the ghost) in the slow movement blocks. 404

Importantly, a specificity of Experiment 2 is that we separated subjects in two groups 405 who performed the slow and fast movement blocks in slightly different contexts, due to 406 a small difference in the Tokens task. That is, the final tokens either jumped every 50 407 ms or every 200 ms, allowing subjects to shorten the trial duration by deciding faster 408 409 in the group performing the task in the former condition (fast decision group) but not in the group using the latter version (slow decision group). Here, the number of trials was 410 always fixed such that shortening the trial duration never allowed to do more trials. Yet, 411 412 by responding faster, subjects could save time and finish the experiment earlier. Even if these specificities remained implicit in this experiment, we expected that they would 413 lead subjects to adjust their decision speed such that it would be generally faster in the 414 fast decision group (n=27; 15 women, 25.1 ± 3.6 years old), and generally slower in 415 the slow decision group (n=27; 17 women, 23.9 ± 2.9 years old). With these two 416 417 groups, we aimed at testing the hypothesis that a default mode of coregulation can be observed when it naturally serves the reward rate; but it would disappear in situations 418 where it is detrimental to the reward rate. As such, we predicted that tapping faster in 419

the fast movement blocks will translate into faster decisions, compared to the decisions 420 in the slow movement blocks, but that this effect will only be observed in the group of 421 subjects incited to make fast decisions but not in the slow decision group where 422 subjects should better favor decision accuracy. Importantly, each subject completed 423 the short version of the UPPS-P Impulsive Behavior (UPPS) scale (Eben et al., 2020). 424 We also evaluated their ability to follow movement instructions in order to make sure 425 that the repartition of participants in the two groups was not creating a bias in our 426 results. The analyses showed no significant difference between the two groups of 427 participants, considering their UPPS scores (see Table S1 in supplementary materials) 428 or their movement performance (see Fig. S2 in supplementary materials). 429

430 Time course of the experiments

Experiments 1 and 2 had a largely similar time course. They both started with a 431 familiarization phase during which subjects performed a neutral block of 10 trials to 432 become acquainted with the basic features of the Tokens task. Subjects were then 433 informed about the two types of blocks they would realize in the experiment. This led, 434 after a phase of calibration (in Experiment 2 only to establish the fast tapping speed), 435 to a training phase during which subjects practiced for 4 blocks (2 blocks of each type), 436 each involving 15 trials (or a few more in fast decision blocks of Experiment 1). The 437 actual experiment then started and involved a total of 18 blocks (9 blocks of each type), 438 439 each involving 26 trials (or a few more in fast decision blocks of Experiment 1). Each block lasted on average 4,36 minutes and a break of 2 to 5 minutes was provided 440 between blocks. 441

Both experiments then ended with blocks consisting of a choice reaction time (CRT) version of the Tokens task. The task in these blocks (always 40 trials) was the same as in the main experiment: subjects had to respond with a left or right index finger tapping movement according to token jumps but here the 15 tokens jumped all at once
in the left or right circle. Experiment 1 entailed 1 CRT block with no restriction on
movement speed (i.e., "free" movements), whereas Experiment 2 entailed 1 CRT block
for each tapping speed (slow or fast) condition, considering that tapping speed may
impact reaction time (RT).

450 **Computational approach**

In our work we simulated the decision data by using an implementation of the urgency
gating model (UGM; Cisek et al., 2009; Thura et al., 2014), in which evidence is
multiplied by a linearly increasing urgency, as follows:

454
$$x_i(t) = E_i(t) \times [gt+b]^+ < T$$
, (3)

where $x_i(t)$ represents the activity of motor neurons at time t in trial i, obtained by 455 multiplying the momentary evidence $E_i(t)$ by an urgency signal. g and b are the slope 456 and the y-intercept of the urgency signal, and []+ denotes half-wave rectification (which 457 set all negative values to zero). To estimate the level of evidence accumulation, we 458 used the computation of the SumLogLR (see above, equation 2) that we low-pass 459 filtered for dealing with intra-trial stimulus noise when calculating evidence such as the 460 evidence accumulation. The accumulation of evidence can thus be expressed as 461 follows: 462

463
$$\tau \frac{dE_i(t)}{dt} = -E_i(t) + (SumLogLR(t) + N(t))$$
(4)

The Term N(t) represents Gaussian noise with a mean of zero and a SD of 0.7 and, we used a linear differential equation with a time constant τ = 200 ms as low-pass filter (Cisek et al., 2009).

The model has three parameters: g, b and T. To fit the data, we performed an 467 exhaustive parameter grid search, with g ranging from 1 x 10^{-7} to 4, b from - 1 to 3 and 468 T from 1 to 3. This was performed separately for each subject and each block condition, 469 and the quality of fit was assessed by using the mean square-error between data 470 distributions of the model and the real data distributions for all decision durations in the 471 interval between 600 and 3000 ms. Importantly, the threshold was not fixed between 472 participants (i.e., ranged from 1 to 3) but was fixed across block conditions (i.e., for fast 473 and slow conditions of the same experiment) to be able to compare the urgency 474 parameters between them. After determining the best fitting parameters for each 475 476 dataset, we generated a subsequent grid search from the average of the gain and slope of all subjects to determine the best pairs of parameters for a given threshold. 477 This procedure was repeated up to 100 times to ensure parameter optimality 478 convergence, we computed the mean shape (linear function based on g and b 479 parameters) of the resulting urgency functions. 480

481 **Data analyses**

Behavioral data were collected by means of custom Matlab scripts (MathWorks,
Natick, Massachusetts, USA). Statistical analyses were performed using JASP
(Wagenmakers et al., 2018) for repeated-measures analyses of variance (ANOVA_{RM}),
t-tests and Spearman's correlations, and using the package gamlj in jamovi (ŞAHİN &
AYBEK, 2020) for linear mixed models.

487 Data processing and definition of endpoint measures

In general, trials with poor performance in the decision phase and/or in the movement
phase of the Tokens task were excluded in both experiments. This concerned trials
with no response before Jump-15 or with an anticipated response (before Jump-3). This

491 also involved removing trials where the pacman was caught by the ghost and, for 492 Experiment 2, also trials in which the participants did not move at the required speed. 493 Finally, the laser sometimes failed to report the index finger movements and these 494 trials were removed too. As a result, overall, 24% of trials were removed for the 495 analyses (17% for Experiments 1 and 31% for Experiment 2). The same procedure 496 was followed to clean the data in the CRT task, which led to an overall removal of 11% 497 of trials (1% and 20% for Experiments 1 and 2, respectively).

The endpoint measures were the same for Experiment 1 and 2. To characterize the 498 speed at which subjects made their choice, we considered the time they took to decide. 499 This decision duration was computed as the average RT in the Tokens task (computed 500 separately for fast and slow blocks with all trial types pooled together) minus the 501 average RT in the corresponding CRT block (Ferrucci et al., 2021). It should be noted 502 that the majority of studies have used the RT in simple reaction time (SRT) tasks to 503 compute the decision duration (Carsten et al., 2023; Cisek et al., 2009; Derosiere et 504 505 al., 2022; Thura, 2020), but as we were using different constraints on movement speed, 506 we chose the CRT in order to obtain a measure of the time required to prepare each type of movement (i.e., for free, fast and slow movements). Indeed, there is some 507 evidence that even if subjects prepare their movement in advance in both the SRT and 508 the CRT tasks, their level of preparation is lower in the CRT than in the SRT (Quoilin 509 et al., 2019). Then, decision accuracy was calculated as the percentage of trials in 510 which subjects choose the correct lateral circle, referred to as %Correct. Thanks to the 511 UGM, we also obtained the intercept and the slope of an urgency signal for each 512 513 participant and each type of block, as an additional primary endpoint measure. These two parameters then enabled us to estimate the evolution of the *urgency level* over 514 time. To characterize the speed at which subjects moved, we considered the time it 515

took for participants to perform the index flexion movements. Hence, *movement duration* corresponds to the mean duration of a single tap averaged over the four
flexions participants performed in each trial of the task.

519 Statistical analyses

520 Experiment 1

- 521 The purpose of this experiment was to further investigate the existence of a shared
- 522 invigoration process linking decision and movement by looking at how contextual
- 523 changes in decision speed influence movement speed.

524 Effect of decision-related instructions on decision endpoint measures

In order to check whether subjects followed instructions and changed their decision 525 policy between fast and slow decision blocks, we first ran paired t-tests on decision 526 duration and decision accuracy. We then considered the urgency signal estimated for 527 each type of block, running a mixed model with BlockType (fast decision, slow 528 decision) as a factor, Time (elapsed during the decision phase) as a covariate and 529 subject number as a cluster variable (Urgency ~ BlockType * Time + (BlockType * 530 *Time*|*Subject*)). Since we hypothesized a relationship between urgency and decision 531 duration that would hold true across subjects, the covariable was not scaled. 532

533 Effect of decision-related instructions on movement endpoint measures

To investigate the context and time-sensitive effect of decision duration, we ran general mixed models on movement duration with BlockType (fast decison, slow decision) as a factor, decision duration as a covariate and subject number as a cluster variable (*Movement duration ~ BlockType * Decision duration + (BlockType * Decision duration|Subject*)). Our hypothesis was that movement and decision duration correlate within- but not necessarily between-subjects. Hence to get rid of individual average
differences in decision duration, we used Z-scores clusterwise to scale the covariable
(i.e., decision duration). Post-hoc comparisons were conducted using t-tests with
Bonferroni correction for multiple comparisons. Monotonic relationships between
block-related changes in movement and block-related changes in urgency/decision
were tested using Spearman's rank correlations.

545 Experiment 2

Here, we aimed at investigating the reverse relationship, as compared to Experiment 1; that is, how contextual changes to movement speed influence decision speed. In addition, this experiment aimed at testing the hypothesis that such a link is masked when detrimental to the reward rate.

550 Effect of movement-related instructions on movement endpoint measures

In order to check whether subjects followed instructions in both groups and changed their movement speed between fast and slow movement blocks, we performed a twoway ANOVA_{RM} on movement duration with BlockType (fast movement, slow movement) and Group (fast decision group, slow decision group) as within-subject factors.

556 Effect of movement-related instructions on decision endpoint measures

The analyses for Experiment 2 were similar to those for Experiment 1, except that here, we looked at the reverse relationship by running a general mixed model on decision duration with BlockType (fast movement, slow movement) and Group (fast decision, slow decision) as factors, movement duration as covariable and subject number as a cluster variable (*Decision duration ~ Group * BlockType * Movement duration + (Group * BlockType * Movement duration|Subject*)).

563 Exploratory investigation of pupil dilation

In Experiment 1, we recorded pupil diameter from 19 of the 62 participants during task 564 performance. However, one participant did not finish the experiment, so pupil data 565 566 were analyzed on 18 participants (11 Women, 24.5 ± 3.7 years old). This allowed us to investigate the involvement of the arousal system (proxied by pupil size) in 567 generating the urgency signal (McGinley et al., 2015; Wagenmakers et al., 2018). To 568 this end, the pupil diameter was acquired with an EyeLink 1000+ eye tracker video-569 based system (SR Research), recording monocularly pupil size (in arbitrary units) and 570 eye movements with a sampling frequency of 1000 Hz. Before analyzing the data, pupil 571 traces were preprocessed to remove eye-blinks, which were identified by the blink 572 detection algorithm implemented Matlab (https://github.com/alexandre-573 in zenon/pupil/), and replaced by linear interpolations. Furthermore, traces were first 574 filtered by a high-pass filter of 0.01 Hz, then downsampled to 10 Hz to facilitate the 575 analysis. In order to characterize block-related changes in pupil size during the 576 577 decision phase, we extracted the peak of pupil dilation following the first flexion initiation in each trial (see Fig. S3 in supplementary materials). We then analyzed these 578 Peak pupil data by means of a mixed model with BlockType (fast decision, slow 579 580 decision) as a factor, decision duration as covariable and subject number as a cluster variable (Peak pupil ~ BlockType * Decision duration + (BlockType * Decision 581 duration Subject). Similarly to the urgency signal analysis, we did not scale the 582 covariable. This analysis allowed us to investigate whether Peak pupil size would 583 evolve as a function of decision duration, as shown for urgency, both in the fast and 584 585 slow decision blocks. Then, in an additional analysis aimed at further characterizing the evolution of Peak pupil size over time elapsed during deliberation, we obtained for 586 each subject the mean Peak pupil dilation in 8 bins of decision duration (from short to 587

long) and fitted these pupil data with a linear regression to obtain an intercept and a slope. These pupil parameters (intercept and slope) were put in relation to those extracted from the urgency signal (intercept and slope) with Spearman's rank correlations.

592 **Results**

593 Experiment 1

594 Subjects adjusted their decision duration according to the block instruction

In this experiment, we had participants perform the Tokens task in fast and slow 595 decision blocks, which required them to favor either decision speed or accuracy, 596 respectively. Consistently, participants took less time to decide in the fast (1647 ± 276 597 598 ms) than in the slow decision blocks (2220 \pm 111 ms; $t_{1,55} = -15.236$, p < 0.001, Cohen's d = - 2.036, see Fig. 2.B). This shortening in decision duration influenced 599 choice accuracy: participants were less accurate when deciding in the fast decision 600 601 blocks (84 \pm 5 % of correct choices) than in the slow decision ones (94 \pm 2 %; t_{1.55}= -14.175, p < 0.001, Cohen's d = - 1.894). These findings indicate that participants 602 followed the instructions by adopting a strategy favoring speed in the fast decision 603 blocks and accuracy in the slow decision blocks. 604

Block-related changes in decision duration were reflected in the level of urgency (Thura et al., 2014; Derosiere et al., 2022). Indeed, the mixed model analysis on the urgency signal revealed a main effect of the factor BlockType (see Fig. 4.A, $F_{1,55} = 101$, p < 0.001): as expected, the level of urgency was on average higher in the fast (0.327 ± 0.166 a.u) than in the slow decision blocks (0.059 ± 0.107 a.u.). Importantly, this effect was also true when considering the decision period in separate temporal bins (see Table S2 in supplementary materials): the urgency level was higher in the fast than in

the slow decision blocks, regardless of the bin considered, up to the last temporal one 612 (all $t_{1.55} > 3.760$, all p < 0.001, all Cohen's d > 0.500). Moreover, the mixed model 613 analysis revealed a significant effect of the factor Time ($F_{1,55} = 112$, p < 0.001), 614 indicating that urgency increased as the time elapsed during deliberation in both fast 615 616 and slow decision blocks, as also previously shown (Cisek et al., 2009; Thura et al., 2014: Derosiere et al., 2022: Murphy et al., 2016: Steinemann et al., 2018). Finally, we 617 observed a significant BlockType x Time interaction ($F_{1,951} = 475$, p < 0.001), 618 suggesting that the time course of urgency differed between the two block types. To 619 further address this point, we considered the intercept and the slope of the urgency 620 621 signal (estimated with the urgency gating model) in both block types. Interestingly, paired-t-tests revealed a significantly higher intercept in fast decision blocks (0.195 ± 622 0.140 a.u.) compared to the slow decision ones (- 0.200 ± 0.251 a.u.; $t_{1,55} = 11.097$, p 623 < 0.001, Cohen's d = 1.483), indicating a greater urgency at decision onset in the 624 former blocks. However, the urgency exhibited a slower increase in the fast than in the 625 slow decision blocks. That is, although the slope was significantly positive in both block 626 types (both $t_{1.55} > 5.000$, both p < 0.001, both Cohen's d > 0.700), it was nevertheless 627 smaller in the fast $(0.097 \pm 0.125 \text{ a.u.})$ than in the slow decision blocks (0.192 ± 0.119) 628 629 a.u.; $t_{1,55} = -5.241$, p < 0.001, Cohen's d = -0.700). Hence, the urgency was generally higher when subjects were in a context promoting fast decisions, with a peak difference 630 at decision onset; from there on urgency increased over time in both block types but 631 632 did so slower in the fast decision blocks, thus reducing the gap with the slow decision blocks, although the difference remained significant until the end of the decision 633 process. 634



636

Figure 4. Results for Experiment 1. A. Urgency signal. The block-related changes in 637 decision duration were reflected in the level of urgency (left panel), with a higher level of 638 639 urgency in fast (blue bar) than slow decision blocks (white bar). Consistent with the literature, 640 the evolution of the urgency signal over time (right panel) depended on the type of block: it 641 was higher at decision phase onset (greater intercept, top left inset) and increased more slowly (lower slope, top right inset) in fast compared to the slow decision blocks. B. Movement 642 duration. Decisions were implemented by shorter (faster) movements in fast decision 643 compared to slow decision blocks (left panel) even if such a coregulation was not beneficial to 644 the reward rate. Notable, we also found that movement duration shortened with increasing 645 decision duration, but this was only true in slow decision blocks (negative slope, the inset) C. 646 **Correlations.** The more participants responded with a high level of urgency in fast decision 647 648 compared to slow decision blocks, the more their movements became shorter (faster) in the fast compared to the slow decision blocks (left panel). Similarly, those participants with the 649 largest reduction in decision duration were also those who shortened their movements the 650 most in the fast compared to the slow decision blocks (right panel). Error bars represent SE. # 651 t-test against 0 p < 0.025. ***p < 0.001. 652

653

654 *Movement duration was influenced by increasing decision urgency*

In this first experiment, we assessed the coregulation hypothesis by investigating the impact of changes in decision urgency on movement duration. Based on this

hypothesis and in line with prior work (Carsten et al., 2023; Thura et al., 2014; Thura, 657 658 2020), we expected that the higher urgency in the fast decision blocks would also fasten the motor response, resulting in shorter (faster) movements in fast decision 659 blocks. Consistently, the mixed model analysis on movement duration revealed a main 660 effect of the factor BlockType ($F_{1.55.1} = 24.46$, p < 0.001), with shorter values in fast (46) 661 \pm 12 ms) than in slow decision blocks (51 \pm 18 ms, see Fig. 4.B). Moreover, the analysis 662 revealed a significant BlockType x decision duration interaction ($F_{1,47.2} = 11.14$, p = 663 0.002). In order to consider further this interaction, we grouped the movement duration 664 data in 8 bins of decision duration (see Fig. 4.B). Then, we calculated a delta on the 665 666 global movement duration of the first and the last bins in order to express the change in movement duration (Delta movement). The same delta was calculated on decision 667 duration (Delta decision) to finally compute a slope representing how much movement 668 duration varied as a function of changes in decision duration (i.e., Delta movement 669 /Delta decision). A negative slope would indicate a shortening of movement duration 670 with increasing decision duration while a positive slope would reflect the opposite 671 relationship, that is, a lengthening of movement duration with decision duration. 672 Interestingly, the slope was negative in the slow decision blocks (- 2.11 \pm 5.14; $t_{1,55}$ = -673 674 3.076, p < 0.025 with Bonferroni correction, Cohen's d = - 0.411 when compared to 0 using Student's t-tests) but it was null in the fast decision blocks (0.438 \pm 2.779; t_{1.55} = 675 1.180, p = 0.243, Cohen's d = 0.158). Consistently, the slope was found significantly 676 lower in the slow than in the fast decision blocks (paired $t_{1,55} = 3.159$, p < 0.01, Cohen's 677 d = 0.422). Hence, altogether the analyses indicate globally shorter movement 678 durations in the fast (higher urgency) than in the slow decision blocks but with an 679 acceleration of movement execution over deliberation time occurring in the latter but 680 not in the former decision blocks. 681

We then continued to investigate the relationship between decision urgency and 682 movement duration by means of correlations. To do so, we computed deltas of 683 movement duration between the fast and slow decision blocks (delta fast-slow decision 684 blocks) and considered the degree to which changes in movement duration between 685 the two block types were related to the instructed changes in decision speed. To 686 characterize the latter, we computed both the delta of urgency and the delta of decision 687 duration, as depicted on the left and right sides of Figure 4.C., respectively. 688 Interestingly, Delta movement duration correlated negatively with Delta urgency (Rho 689 = - 0.343, p = 0.01, 95%-confidence intervals [CI] = [-0.553, - 0.079]), indicating that 690 691 the more urgency got high in fast compared to slow decision blocks (higher delta values), the more movements became short (fast) in this type of block (lower delta 692 values). Considering deltas in decision duration instead of urgency led to the same 693 result, which here was manifest as a positive correlation (Rho = 0.364, p = 0.006, CI = 694 [0.114, 0.577]): the more subjects shortened their decision duration in fast compared 695 to slow decision blocks (lower deltas), the more the movements became shorter (lower 696 deltas). Altogether, these findings are consistent with a coregulation of decision and 697 movement speed (Carsten et al., 2023; Spieser et al., 2017; Thura, 2020). 698

699 Experiment 2

700 Subjects adjusted their movement duration according to the block instruction

In this experiment, we had participants perform the Tokens task in fast and slow movement blocks, which required them to report their decision with either fast or slow index finger flexions. Consistent with these instructions and as shown on Figure 3.B, the ANOVA_{RM} revealed that movements were on average of shorter duration in the fast $(37 \pm 11 \text{ ms})$ than in the slow movement blocks (59 ± 24 ms; F_{1,53} = 106.879, p < 0.001, partial eta-squared (η_P^2) = 0.673). Moreover, participants in this experiment were split in two groups where they were implicitly encouraged to either favor decision speed (fast decision group) or decision accuracy (slow decision group). Participants in both groups displayed equivalent movement durations according to the specific instructions of the two block types, as indicated by the absence of factor Group or BlockType X Group interaction on movement duration (all $F_{1,53} = [0.111, 1.257]$, p = [0.267, 0.740], $\eta_{P}^2 = [0.002, 0.024]$).

713 Decision duration was influenced by movement duration

In this experiment, we assessed the coregulation hypothesis by investigating the 714 715 impact of block-related changes in movement duration on decision urgency. Based on this hypothesis and in line with prior work (Carsten et al., 2023; Kita, et al., 2023.), we 716 717 expected that the requirement to move fast would naturally increase the urgency, resulting in shorter (faster) decisions in fast than slow movement blocks. Yet, as 718 explained in the introduction, we expected that this should only occur if such a 719 720 coregulation is not detrimental to the reward rate. In other words, we predicted that moving faster in the fast movement blocks would only translate into faster decisions 721 (higher urgency) in the group favoring decision speed anyway (fast decision group) but 722 723 not in the group prioritizing decision accuracy (slow decision group).

Unsurprisingly, the mixed model analysis revealed a significant effect of the factor 724 Group on decision duration ($F_{1.55,9} = 6.32$, p = 0.015). As such, decision durations were 725 shorter in the fast decision group (1997 \pm 175 ms) than in the slow decision group 726 (2104 ± 158 ms), as implicitly promoted in this experiment. Furthermore, we found a 727 significant Group x BlockType interaction on decision duration ($F_{1,143,3} = 6.82$, p = 728 0.010; see Fig. 5.A). As such, changes in movement duration from the slow to the fast 729 movement blocks elicited distinct effects on decision duration depending on the group. 730 731 That is, post-hoc analyses revealed that participants in the fast decision group made shorter decisions in fast (1990 ± 183 ms) than slow movement blocks (2004 ± 170 ms; t_{161.1} = 2.957, p < 0.025 with Bonferroni correction). Such an effect was not found in the slow decision group, where decision durations were not significantly different between the fast (2112 ± 164 ms) and slow movement blocks (2096 ± 154 ms; t_{126.4} = - 0.667, p = 1.000). Hence, faster movements led participants to decide faster when such a coregulation was consistent with their task goal, in the fast decision group, but not when it would have been detrimental, in the slow decision group.

The mixed model analysis also revealed a main effect of the factor movement duration 739 $(F_{1,16459.4} = 8.21, p = 0.004)$ on decision duration. Similar to the analysis run in 740 Experiment 1, we grouped decision duration in bins of movement duration (here we 741 used 4 bins) in order to calculate a delta between the first and the last bins on decision 742 (Delta decision) and movement durations (Delta movement). These deltas were then 743 used to compute a slope expressing changes in decision duration as a function of 744 changes in movement duration (Delta decision/Delta movement). A Student's t-test 745 against 0 showed that the slope was significantly negative ($t_{1,53} = -3.152$, p < 0.01, 746 Cohen's d = - 0.429) indicating that long movement durations were associated with 747 short decision durations. However, this effect interacted with the factor Group 748 (Movement duration x Group $F_{1,16459.4} = 5.00$, p < 0.05). More precisely, following 749 Student's t-tests against 0, the slope was significantly negative in the fast decision 750 group (- 4.606 ± 5.824 ; $t_{1,26} = -4.109$, p < 0.001, Cohen's d = - 0.791) but not in the 751 slow decision group (-0.177 ± 4.392 ; $t_{1,26} = -0.210$, p = 0.835, Cohen's d = -0.040). 752 This suggests that, only in the fast decision group, movement duration varied as a 753 754 function of deliberation time, as observed in Experiment 1. All other effects of the mixed model were nonsignificant ($p = [0.092 \ 0.509]$). 755



756

Figure 5. Results for Experiment 2. A. Decision duration. As expected, participants in the 757 fast decision group made faster decisions than those in the slow decision group (left panel). 758 759 Moreover, as also shown on the left panel, only in the fast decision group were decision durations affected by the movement block type, with shorter (faster) decisions accompanying 760 761 faster movements (red bar). On the right panel you can also see that long movement durations 762 were associated with short decision durations only in fast decision group (see insets displaying 763 specifically the slope in the fast and slow decision groups). B. Urgency signal. The overall 764 urgency level did not differ significantly between the two groups and the two types of block (left 765 panel). However, as shown on the right panel, its evolution over time differed between the two groups of subjects. More precisely, the movement block type affected the intercept and the 766 slope of the urgency signal in the fast decision group with only a marginal effect on the slope 767 768 in the slow decision group. Indeed, the urgency signal was higher at the decision phase onset (greater intercept, top left inset) and increased more slowly (lower slope, top right inset) in fast 769 770 (red bar) block relative to slow (black bar) movement blocks in the former group only. Error bars represent SE. # t-test against 0 p < 0.05, *p < 0.05, ***p < 0.001. 771

772

We then assessed the impact of varying the movement speed in the two different block

types on decision urgency itself (see Fig. 5.B). The mixed model analysis revealed a

main effect of the factor Time on the urgency signal, consistent with an increasing 775 776 urgency over time ($F_{1,47,9}$ = 197.94, p < 0.001). Moreover, we found that this main effect interacted with the factor BlockType, indicating that the urgency signal generally 777 increased faster in slow relative to fast movement blocks (BlockType x Time 778 interaction; $F_{1,916} = 266.65$, p < 0.001). Most interestingly, this interaction depended on 779 the Group (Group x BlockType x Time interaction; $F_{1.916} = 32.30$, p < 0.001). To better 780 understand this triple interaction, we ran further analyses on the intercept and the slope 781 of the urgency signal (as in Experiment 1). More precisely, paired t-tests revealed a 782 higher urgency intercept in fast $(0.013 \pm 0.186 \text{ a.u.})$ than slow movement blocks (-783 784 0.053 ± 0.215 a.u.; $t_{1.26} = 2.854$, p < 0.01, Cohen's d = 0.549) for the fast decision group, whereas the urgency intercept was around 0.093 ± 0.163 a.u. in both block 785 types for the slow decision group ($t_{1,26} = 0.915$, p = 0.369, Cohen's d = 0.176). Hence, 786 787 urgency was greater at the decision onset in the fast than in the slow movement blocks only for the fast decision group. Yet, it seems that urgency then increased more slowly 788 in fast movement blocks, especially in fast decision group. Indeed, for this group, the 789 urgency slope was lower in fast (0.110 \pm 0.079; t_{1,26} = - 3.645) than slow movement 790 blocks (0.147 \pm 0.103 a.u.; $t_{1,26} = -3.645$, p = 0.001, Cohen's d = -0.701). The 791 792 difference between fast $(0.160 \pm 0.061 \text{ a.u.})$ and slow movement blocks (0.178 ± 0.078) a.u.) was still present in the slow decision group, although smaller and marginal ($t_{1,26}$ 793 = -1.83, p = 0.079, Cohen's d = -0.351). In other words, the urgency signal was higher 794 795 at the decision phase onset (greater intercept) and increased slower (lower slope) in fast relative to slow movement blocks in the group pushed to decide quickly while it 796 797 remained mostly unchanged between the two block types in the group pushed to decide slowly. All other effects of the mixed model were nonsignificant (p = [0.154]798 799 0.558)). These results suggest that the instruction to boost movement speed in the fast

movement blocks induced a parallel increase of urgency when this was consistent with the task goals, in the fast decision group. By contrast, boosting movement speed did not have such an effect in the slow decision group, when it would have been detrimental. In this case, the subjects decided at a similar speed during both slow and fast movement blocks.

Finally, we investigated how the switch in movement speed between fast and slow 805 806 movement blocks impacted urgency and decision duration. To do so, we computed, as in the Experiment 1, the deltas between the fast and slow movement blocks (delta 807 fast-slow movement blocks) and looked at how Delta urgency and Delta decision 808 duration correlated with Delta movement duration in both decision groups, as depicted 809 on Figure 6. Interestingly, their relationship differed from the Experiment 1. In the fast 810 decision group, there was no relationship with Delta movement duration whether we 811 considered the Delta urgency (Rho = 0.217, p = 0.276, CI = [- 0.191, 0.538]) or the 812 Delta decision duration (Rho = -0.105, p = 0.601, CI = [-0.451, 0.318]). In the slow 813 814 decision group, we also found no significant correlation between Delta urgency and Delta movement duration (Rho = 0.176, p = 0.377, CI = [- 0.213, 0.539]). Surprisingly, 815 we found in this group a relationship between changes in movement duration and 816 817 decision duration, but here Delta decision duration correlated negatively with Delta movement duration (Rho = -0.510, p = 0.007, Cl = [-0.779, -0.141]), suggesting that 818 participants with shorter movements in fast relative to slow movement blocks (lower 819 deltas) were those who waited the longest to make their decisions (higher deltas). 820



821

Figure 6. Correlations for Experiment 2. For the fast decision group (upper panel), we did not find any relationship between block-related changes in movement duration (Ranks of Delta movement) and block-related changes in decision features, whether we considered changes in urgency level (Ranks of Delta urgency, left) or changes in decision duration (Ranks of Delta decision, right). For the slow decision group (lower panel), Delta Movement did not correlate with Delta urgency (left) but correlated negatively with Delta decision (right).

828

In summary, our data in Experiment 2 also indicate a natural coregulation between decision and movement speed when considering the fast decision group in Experiment 2. In contrast, movement speed instructions in the slow decision group did not seem to have any impact on decision speed or on urgency. If anything, the correlations revealed a negative relationship between block-related changes in movement and
decision speed in that group favoring accuracy in Experiment 2.

835 Analyses of pupil dilation

836 Pupil dilation increased with both urgency and accuracy requirements

Previous studies have shown that increases in urgency induce pupillary dilation (Gross 837 838 & Dobbins, 2021; Murphy et al., 2016; Reppert et al., 2023; Steinemann et al., 2018). 839 However, the link between pupil dilation and decision urgency is still much debated in the literature. That is, while some have suggested that pupil dilation reflects the 840 841 involvement of the arousal system in the generation of the urgency signal (Murphy et al., 2016), others have proposed that the urgency-related pupillary dilation rather 842 results from an increased recruitment of the arousal system to ensure decision 843 accuracy under time pressure (Steinemann et al., 2018). In order to directly address 844 this question in the current study, we analyzed pupil dilation as a function of decision 845 duration, in 18 of the subjects who took part in Experiment 1. 846

The mixed model on Peak pupil dilation did not reveal any significant effect of the factor 847 BlockType ($F_{1,8257} = 0.616$, p = 0.433; 111 ± 57 a.u. for fast decision blocks and 163 ± 848 74 a.u. for slow decision blocks; see Fig. 7). However, the analysis revealed a main 849 effect of the factor decision duration ($F_{1,8265} = 30.173$, p < 0.001), indicating that pupil 850 dilation increased with decision duration in both types of blocks. Interestingly, this effect 851 interacted with the factor BlockType (BlockType x decision duration interaction; F_{1,8265} 852 = 30.173, p < 0.001). In order to understand this interaction, we estimated the intercept 853 854 and slope of the pupil function in each block type by means of linear regressions (see related section in Methods for more details) and compared them across block types. 855 The intercept, which thus reflects pupil size at the onset of the decision phase did not 856

differ between block types ($t_{1,17} = 1.049$, p = 0.309, Cohen's d = 0.247; 85 ± 71 a.u. 857 and 50 ± 152 a.u. in fast and slow decision blocks). However, the slope (reflecting the 858 speed at which the pupil expanded over decision duration) was steeper in slow (50 ± 859 152 a.u.) relative to fast decision blocks (5 \pm 71; t_{1,17} = - 2.107, p = 0.05, Cohen's d = -860 0.497). This result was supported by multiple paired t-tests (Bonferroni corrected) 861 looking at the difference in Peak pupil dilation between fast and slow decision blocks 862 in the 8 bins of decision duration. As such, this additional analysis showed that, in early 863 bins, pupil dilation did not differ significantly between block types but that it became 864 progressively larger in slow than fast decision blocks in the last bins of decision 865 duration (see Table S3 in supplementary material). 866



867

Figure 7. Peak pupil data in Experiment 1 (n=18). Peak pupil dilation was comparable in 868 fast (blue bar) and slow (white bar) decision blocks (left panel). Consistent with the literature, 869 Peak pupil dilation increased with decision duration in both types of blocks (right panel). 870 However, while the pupil dilation seemed similar between the two types of block at the 871 beginning of the decision phase (similar pupil intercepts, top left inset), its dilation tended to 872 increase faster in slow decision blocks relative to fast decision ones (higher pupil slope, top 873 right inset), leading to a progressively more dilated pupil in the former. Error bars represent 874 SE. 875

To further investigate the link between pupil dilation and urgency, we put into relation 877 the block-related changes in parameters of both functions. In other words, we looked 878 at how block-related changes in pupil intercept (slope) were linked to block-related 879 changes in urgency intercept (slope). These changes were quantified by obtaining 880 delta values (delta fast-slow decision blocks) for the intercept and slope of both the 881 pupil (Delta pupil intercept and Delta pupil slope) and urgency (Delta urgency intercept 882 and Delta urgency slope) functions in all subjects, with thus positive deltas indicating 883 greater values in fast than slow decision blocks. Interestingly, a Spearman correlation 884 on Delta intercept values revealed a tendency toward a positive correlation (Figure 8; 885 Rho = 0.459, p = 0.057, CI = [0.012, 0.779]), suggesting that participants who showed 886 a greater urgency increase at the onset of decisions in fast than slow decision blocks 887 were also those displaying the larger increase in pupil dilation. Moreover, a positive 888 correlation was found when considering the Delta slope values (Rho = 0.478, p = 889 0.047, CI = [- 0.022, 0.803]), indicating that participants whose urgency signal 890 increased more over time in fast relative to slow decision blocks also showed a larger 891 increase in pupil dilation over time. 892



Figure 8. Correlations for Peak pupil data in Experiment 1 (n=18). Block-related changes
 in the intercept and slope of the Peak Pupil function (Ranks of Delta pupil intercept and slope)
 were related to block-related changes in the same parameters of the urgency function (Ranks

of Delta urgency intercept and slope). That is, the participants showing a greater increase in pupil intercept (slope) in fast compared to slow decision blocks were also those showing a greater increase in urgency intercept (slope).

900

Altogether, the effects described above are consistent with a tight relationship 901 between urgency and pupil dilation. Indeed, both urgency and pupil dilation clearly 902 increased with decision duration, and more so in slow decision blocks. Moreover, 903 block-related increases in urgency intercept and slopes were associated with parallel 904 enlargements in pupil size (though marginal for the intercept). However, we also found 905 that, pupil size tended to be smaller in fast than in slow decision blocks (and 906 significantly so in later bins), contrary to urgency which showed the reverse effect. 907 Such an effect on the Peak pupil data was not related to differences in baseline (tonic) 908 909 levels of pupil dilation as these values were equivalent in both block types (see Fig. S4 in supplementary materials). Nor was this effect due to the fact that decision durations 910 differed across block types within the same bins (see Fig. 7). Indeed, when considering 911 912 only a set of equivalent ambiguous trials with long decision durations (i.e., decisions 913 falling between Jump₋₉ and Jump₋₁₀) and a constant level of evidence (i.e., with a success of probability at decision time equal to 0.8125 in all trials), we found that pupil 914 dilation remained greater in slow decision blocks, although the difference with fast 915 decision blocks was marginal (137 \pm 70 a.u. and 105 \pm 54 a.u., respectively; t_{1,15} = 916 1.97, p = 0.067, Cohen's d = 0.493; 2 subjects had to be excluded from this analysis, 917 because of a lack of data). 918

We then considered the possibility that the larger pupil size observed in slow decision blocks was due to a special focus on accuracy in this condition. As such, subjects had a fixed number of trials here (contrary to fast decision blocks) and they then plausibly recruited all available resource's to be as accurate as possible, including

increased arousal. To test this hypothesis, we considered again the subgroup of 923 ambiguous trials described above for which we computed a block-related delta (fast-924 slow) for the accuracy and pupil data. Interestingly, in those particular trials, the Delta 925 pupil size was positively correlated with the Delta accuracy (Rho = 0.758, p < 0.001, 926 CI = [0.501, 0.873]). In other words, the more the pupil was dilated in the slow decision 927 blocks compared to the fast decision blocks (i.e., the more the delta pupil was 928 negative), the more subjects exhibited better accuracy in the slow than in the fast 929 blocks (i.e., the more the delta accuracy was negative). In conclusion, variations in 930 pupil-related arousal in the current study seemed to be driven by two overlapping 931 factors: the level of urgency, as expected, and the strategic allocation of resources to 932 933 promote accuracy.

934



935

Figure 9. Peak pupil data in ambiguous trials of Experiment 1 (n=16). Peak pupil dilation 936 937 tended to be larger in slow decision blocks (white bar) than in fast decision blocks (blue bar). Given that deltas were computed by measuring the difference in peak pupil dilation between 938 fast and slow conditions, the more the subjects showed a greater peak pupil in slow decision 939 blocks, the more they displayed a negative delta, which corresponds to a low rank value. 940 Interestingly, we found that the greater this pupil enlargement in slow compared to fast decision 941 blocks (i.e., lower rank value), the greater the gain in accuracy in slow compared to fast 942 decision blocks (i.e., lower rank value). 943

944 Discussion

The aim of our study was to provide a principled explanation to the relation 945 between decision and movement speed. Consistent with this, our data supports the 946 947 hypothesis that coregulation operates as a default mode. However, our findings also show that this form of control can fade or even be replaced by a tradeoff relationship, 948 depending on the task goals. Based on these behavioral observations, we propose 949 that several processes come into play to shape the speed of our decisions and 950 movements either selectively or jointly, the latter mode being best observed when a 951 default coregulation of decision and movement allows to maximize the reward rate, or 952 at least, when it is not detrimental to it. 953

954 *The relationship between decision and movement speed adapts to context-*955 *dependent task goals*

Context-dependent changes in decision speed, as elicited in Experiment 1, led 956 to clear changes in movement speed that are consistent with a coregulation of both 957 levels of control. Indeed, subjects made faster movements in fast decision blocks than 958 in slow decision blocks, and these changes in movement speed were correlated with 959 960 the strength of changes in decision speed: the more subjects adjusted their decision speed according to the instruction, the more they showed a parallel change in 961 movement speed. Note that, similar to Carsten et al (2023), changes in movement 962 speed accompanied block-related variations in decision speed despite its absence of 963 impact on the reward rate, substantiating the view that such coregulation type of control 964 965 occurs naturally.

Context-dependent changes in movement speed, as required in Experiment 2,
also affected decision speed. Yet, the direction of the effect differed according to the

group that was considered. That is, the group whose reward rate was maximized by a 968 969 strategy favoring decision speed (i.e., the fast decision group) showed faster decisions in fast movement compared to slow movement blocks. Even if this coregulation effect 970 was not as strong as in Experiment 1, it was still significant, pointing to a similar form 971 of coregulation. In contrast, the group whose reward rate was maximized by a strategy 972 favoring decision accuracy (i.e., the slow decision group) did not show such a 973 974 covariation of decision speed between the slow and fast movement blocks. Quite the contrary, in this group we even observed the reverse relationship. More precisely, 975 although decision speed was similar between fast and slow movement blocks, the 976 977 changes in movement speed correlated negatively with changes in decisions speed: 978 the more subjects accelerated their movement speed in fast compared to slow movement blocks, the more they slowed down their decision. This is consistent with a 979 980 tradeoff type of relationship in this (slow decision) group, contrasting with the coregulation effect observed in the other (fast decision) group, despite the fact that 981 subjects from both groups displayed a coregulation effect when manipulating decision 982 speed in Experiment 1. 983

Interestingly, similar observations regarding context-dependent variations in 984 985 Experiments 1 and 2 were made when considering directly the relationship between movement speed and decision urgency itself (and not only decision speed), as done 986 for the first time in this study. As such, in Experiment 1, the decision urgency was 987 clearly higher in fast decision blocks compared to slow decision blocks and this 988 upregulation was found to significantly correlate with the changes in movement speed 989 990 that occurred between the two contexts: the greater the context-dependent increase in urgency level, the more subjects accelerated their movement speed from one block 991 type to the other. Similarly, the coregulation observed in the fast decision group of 992

Experiment 2 was also apparent when considering the urgency: fast movement blocks 993 were associated with a higher urgency intercept than slow movement blocks in this 994 group of individuals. Such a relationship was not found when the other (slow decision) 995 group was considered. Hence, altogether, these findings indicate that the relationship 996 between decision speed/urgency and movement speed can shift from a coregulation 997 to a tradeoff according to the task goals, which provides an explanation for the 998 apparent discrepancy between findings of past studies (Carsten et al., 2023; Kita et 999 al.,2023.; Reynaud et al., 2020; Saleri Lunazzi et al., 2021). 1000

1001 The deliberation time impacts on movement speed

In our experiment, the level of urgency did not only vary in a context-dependent 1002 1003 manner (i.e., between blocks) but also in a time-dependent manner (i.e., over the course of a trial). That is, as shown in many past studies, urgency increased during a 1004 trial, pushing the subjects to respond as the trial comes to an end. Consistent with a 1005 1006 natural coregulation of decision speed and movement, we observed a time-dependent speeding up of movements over the course of a trial, as already reported in past 1007 studies (Thura et al., 2014; Thura, 2020; Thura et al., 2012). Interestingly, this was 1008 1009 generally true, whether considering results from Experiment 1 or Experiment 2: overall, movement speed increased as deliberation time (and thus urgency) increased, in a 1010 given context. 1011

Yet, an intriguing finding here, is that in Experiment 1, this effect was only observed in the slow decision blocks (generally associated with slow movements) but not in the fast decision blocks (where movements were generally faster due to the context-dependent change in urgency elicited by the task instruction to decide fast). A possible explanation for this is that the slope of the urgency function was smaller in the fast than slow decision blocks of this experiment, as shown in the past. That is, when

subjects put the emphasis on decision speed, the intercept is higher but then the 1018 urgency increases more slowly as evident by a smaller slope in fast decision blocks 1019 (Thura et al., 2014; Thura, 2020). Hence, the weaker increase in urgency over the 1020 course of the trial in the latter block type may be responsible for the absence of time-1021 1022 dependent effect on movement speed in that condition, compared to the slow decision blocks where the slope is steeper following a lower intercept. Nevertheless, previous 1023 1024 studies have shown an acceleration of movements with the passage of time, irrespective of the slope size of the urgency signal (Thura et al., 2014; Thura, 2020). 1025 1026 Another plausible explanation is that the impact of urgency on movement speed is 1027 counteracted by a process controlling the energy cost. More precisely, the energy expenditure as a function of movement duration is represented by a concave upward 1028 function for many types of movement (Shadmehr et al., 2016; Steudel-Numbers & 1029 Wall-Scheffler, 2009; Yoon et al., 2018; Zarrugh et al., 1974). As the speed of 1030 movement is slower in the slow decision blocks than in the fast decision blocks, it is 1031 possible that accelerating the movement speed decreases energy expenditure in the 1032 former and increases it in the latter. Increasing the energetic cost of movement in the 1033 1034 fast decision blocks would lead to a decrease in the value of the reward, and thus the 1035 rate of reward. Therefore, limiting the impact of the urgency signal depending on the energy cost seems entirely credible. The fact that previous studies did not observe a 1036 ceiling effect for the urgency signal could be linked to the type of movement involved 1037 1038 in the task. Indeed, in these studies, the task involved reaching movements, whereas our experiment required index finger tapping movements. Unlike the latter, reaching 1039 1040 movements are large and involve several joints (at least the three articulations of the arm). It is likely that such multi-joint movements offer a wider range of movement 1041 speeds than single-joint (tapping) movements. 1042

Pupil dilation reflects an increase in arousal related to urgency and decision accuracy

Converse to previous studies (Gross & Dobbins, 2021; Murphy et al., 2016; 1045 1046 Steinemann et al., 2018), the pupil dilation did not differ significantly between fast and slow decision blocks. However, we found an increase in dilation as a function of 1047 decision duration, suggesting that pupil dilation may be partly linked to the urgency 1048 signal (Gross & Dobbins, 2021; Lawlor et al., 2023; Murphy et al., 2011, 2016; 1049 Steinemann et al., 2018). This idea is supported by the similarity found between pupil 1050 dilation and urgency signal as well as the positive correlations that were found between 1051 1052 their parameters (see Fig. S5 in supplementary material). Yet surprisingly, unlike the urgency signal, pupil size tended to be more dilated in slow compared to fast decision 1053 blocks. Contrasting with previous studies (Gross & Dobbins, 2021; Murphy et al., 2016; 1054 Steinemann et al., 2018), this result suggests a recruitment of the arousal system as a 1055 function of both urgency and accuracy. One possible explanation is that the emphasis 1056 1057 on decision accuracy in slow decision blocks was particularly high in our design. This pressure could arise from the fact that using a fixed number of trials limits the possibility 1058 of increasing the rate of reward, giving importance to each trial. The positive correlation 1059 1060 between pupil dilation and performance in ambiguous trials supports this idea, showing that the more the pupil was dilated in slow decision blocks, the more subjects increased 1061 their accuracy in this condition for a same level of evidence. 1062

Altogether, these results suggest that pupil dilatation reflects two overlapping actions. More precisely, the recruitment of the arousal system would, on the one side, increase the gain of sensory information at the decision level with the increase in urgency in the fast decision blocks, and on the other side, increase the attention to enhance accuracy in a context where it is prioritized regardless of urgency, as in our slow decision blocks. 1068 The mechanisms through which the arousal system can enhance performance accuracy are still unclear, but may involve enhancing processing of sensory 1069 information (Zénon, 2019). This hypothesis is in line with a report by Steinemann and 1070 his colleagues, who showed that pupil dilation is associated with better encoding of 1071 1072 sensory evidence in the visual cortex. Nevertheless, further studies are needed to investigate the involvement of the arousal system in decision making using causal 1073 approaches, using for example techniques such as transcutaneous vagus nerve 1074 stimulation (Hilz, 2022). 1075

Several neural mechanisms are likely to shape the relationship between decision and movement speed

1078 Plausible neural source underlying the natural coregulation of decision speed and 1079 movement speed

A possible candidate for the coregulation effects observed in our two 1080 1081 experiments is the basal ganglia (Chen & Yang, 2021; Dudman & Krakauer, 2016; Kaduk et al., 2023; Desmurget & Turner, 2010). As such, this structure could be at the 1082 source of a signal invigorating behavior as a whole to maximize reward rate, as 1083 1084 hypothesized in several studies of the last decade (Carsten et al., 2023; Cisek & Thura, 2022; Thura, 2020; Thura et al., 2022; Thura & Cisek, 2017). Reward-sensitivity of the 1085 1086 dopaminergic system has been extensively studied in the past (Berridge & Robinson, 2016; Salamone & Correa, 2024; Schultz et al., 2017; Weinstein, 2023) Consistently, 1087 dopamine seems strongly implicated in the control of decision speed and movement 1088 1089 vigor (Bourgeois et al., 2016; Coddington & Dudman, 2019; Niv, 2007; Pietro Mazzoni et al., 2007). Interestingly, it is believed that it amplifies motor gain (Park et al., 2020; 1090 1091 Yttri & Dudman, 2018), which seems to rely, at least in part, on inhibitory influences 1092 increasing the signal-to-noise ratio in motor neural activity (Duque et al., 2017;

Greenhouse, 2022; Vassiliadis et al., 2020; Wilhelm et al., 2022). This dopaminemediated invigoration may be thus responsible for the increased surround inhibition, a phenomenon observed in studies applying transcranial magnetic stimulation (TMS) during movement preparation, which has traditionally been associated with an increase in movement vigor (Dudman & Krakauer, 2016; Shadmehr et al., 2019) but which has also recently been linked to an increase in decision urgency (Derosiere et al., 2022).

Neural source underlying the occurrence of a tradeoff between decision urgency andmovement speed

1101 The context-dependent modulations of decision speed as a function of the movement blocks in the slow decision group of Experiment 2 reflects a tradeoff rather 1102 than a coregulation of decision and movement speed, despite the fact that there is 1103 evidence for a coregulation in this same group in Experiment 1 (see Fig. S6 in 1104 supplementary materials). This suggests that the requirement to focus on decision 1105 1106 accuracy led this group of subjects to recruit processes allowing to maintain the appropriate level of accuracy despite the fact that switching from slow to fast movement 1107 blocks let to a joint invigoration of decision with movement speed. Such hypothesis is 1108 1109 supported by a negative correlation found between the UPPS score for urgency and the delta of decision duration in the slow decision group (see Fig. S.7 in supplementary 1110 material). Although marginally nonsignificant (p-tendency of 0.083), this correlation 1111 suggests that the more impulsive the subjects (higher UPPS urgency score), the less 1112 they were able to slow down their decisions (lower delta) in fast movement blocks. In 1113 other words, this suggests lesser ability to counteract the effect of common 1114 invigoration. Therefore, it is plausible that a cognitive control process (less efficient in 1115 impulsive individuals) can come into play and selectively shape decision parameters 1116 in a goal-directed manner, helping to "hold your horses". This type of inhibitory control 1117

mechanism has been widely studied during conflict resolution and during action 1118 stopping as an extreme case of braking (Frank et al., 2007; Mosher et al., 2021). 1119 Several lines of evidence indicate that it relies on the hyperdirect pathway from medial 1120 frontal cortex to subthalamic nucleus (Cavanagh et al., 2011; Forstmann et al., 2008; 1121 Herz et al., 2017), producing broad, non-specific inhibition in motor areas to slow down 1122 the action selection process (Aron et al., 2016; Duque et al., 2016; Klein et al., 2014; 1123 1124 Wessel & Aron, 2017). This effect would be associated with a broad motor cortex suppression as already observed in past TMS studies, showing for instance reduced 1125 excitability in leg muscles during cautious finger responses (Derosiere et al., 2022; 1126 1127 Duque et al., 2017).

1128 **Conclusion**

In conclusion, the interaction between decision and movement speed seems 1129 influenced by different mechanisms. Our findings highlight two of them; a common 1130 1131 invigoration mechanism responsible for a natural coregulation between decision and movement speed, and a cognitive mechanism, which slows down decisions when the 1132 reward is linked to the precision of the choices. Contrary to expectations, although the 1133 urgency signal was influenced by changes in movement speed, it did not always 1134 correlate with it, suggesting that this signal reflects a combination of the different 1135 mechanisms involved in decision making and not just that of invigoration. Interestingly, 1136 our results support a link between pupil dilation and decision urgency, but here also 1137 with the additional influence of an accuracy-promoting factor. 1138

1139

1140

1142 Acknowledgements

The authors wish to thank Julien Lambert, Benvenuto Jacob, Christian Lebègue, Caroline Quoilin and Justine Hupin for their contribution to the development of the task design. We thank also David Thura for his help on data modeling in the Tokens Task, as well as Claudia Danse, Eline Volders, Baptiste Waltzing and Fanny Schannes for their help with data acquisition.

1148

1149 **Declaration of interests**

1150 The authors declare no competing interests.

1151

1152 Author contributions

FF designed the study, acquired and analyzed the data, and wrote the first draft of the manuscript. IC contributed to the study design and data analyses, TC and GD contributed to the study design, AZ contributed to the data analyses, and JD contributed to the study design and data analyses. All authors contributed to the article and approved the submitted version.

1158 Grants

This work was supported by grants from the Belgian National Funds for Scientific Research (FNRS; PDR INHIB-IT) and from the UCLouvain (FSR). FF was a doctoral student supported by the Fund for Research training in Industry and Agriculture (FRIA/FNRS: FC29718; Fonds pour la Formation à la Recherche dans l'Industrie et dans l'Agriculture) and from the WBI- World Excellence. JD was supported by grants from the Belgian FNRS (F.4512.14).

1165

1166

1168 **References**

- Aron, A. R., Herz, D. M., Brown, P., Forstmann, B. U., & Zaghloul, K. (2016).
 Frontosubthalamic Circuits for Control of Action and Cognition. *The Journal of Neuroscience*, *36*(45), 11489-11495. https://doi.org/10.1523/JNEUROSCI.234816.2016
 Detriction of Control of Action and the incentive constituation
- Berridge, K. C., & Robinson, T. E. (2016). Liking, wanting, and the incentive-sensitization
 theory of addiction. *American Psychologist*, *71*(8), 670-679.
- 1175 https://doi.org/10.1037/amp0000059
- Bourgeois, A., Chelazzi, L., & Vuilleumier, P. (2016). Chapter 14—How motivation and
 reward learning modulate selective attention. In B. Studer & S. Knecht (Éds.), *Progress in Brain Research* (Vol. 229, p. 325-342). Elsevier.
- 1179 https://doi.org/10.1016/bs.pbr.2016.06.004
- Carland, M. A., Thura, D., & Cisek, P. (2019). The Urge to Decide and Act : Implications for
 Brain Function and Dysfunction. *The Neuroscientist*, *25*(5), 491-511.
 https://doi.org/10.1177/1073858419841553
- Carsten, T., Fievez, F., & Duque, J. (2023). Movement characteristics impact decisionmaking and vice versa. *Scientific Reports*, *13*(1), 3281.
 https://doi.org/10.1038/s41598-023-30325-4
- Cavanagh, J. F., Wiecki, T. V., Cohen, M. X., Figueroa, C. M., Samanta, J., Sherman, S. J.,
 & Frank, M. J. (2011). Subthalamic nucleus stimulation reverses mediofrontal
 influence over decision threshold. *Nature Neuroscience*, *14*(11), 1462-1467.
 https://doi.org/10.1038/nn.2925
- 1190Charnov, E. L. (1976). Optimal foraging, the marginal value theorem. Theoretical Population1191Biology, 9(2), 129-136. https://doi.org/10.1016/0040-5809(76)90040-X
- Chen, X., & Yang, T. (2021). A neural network model of basal ganglia's decision-making
 circuitry. *Cognitive Neurodynamics*, *15*(1), 17-26. https://doi.org/10.1007/s11571-020 09609-2
- Churchland, A. K., Kiani, R., & Shadlen, M. N. (2008). Decision-making with multiple
 alternatives. *Nature Neuroscience*, *11*(6), 693-702. https://doi.org/10.1038/nn.2123
- Cisek, P., Puskas, G. A., & El-Murr, S. (2009). Decisions in Changing Conditions : The
 Urgency-Gating Model. *The Journal of Neuroscience*, *29*(37), 11560-11571.
 https://doi.org/10.1523/JNEUROSCI.1844-09.2009
- Cisek, P., & Thura, D. (2022). Models of Decision-Making Over Time. In P. Cisek & D. Thura,
 Oxford Research Encyclopedia of Neuroscience. Oxford University Press.
 https://doi.org/10.1093/acrefore/9780190264086.013.346
- Coddington, L. T., & Dudman, J. T. (2019). Learning from Action : Reconsidering Movement
 Signaling in Midbrain Dopamine Neuron Activity. *Neuron*, *104*(1), 63-77.
 https://doi.org/10.1016/j.neuron.2019.08.036
- Derosiere, G., Thura, D., Cisek, P., & Duque, J. (2019). Motor cortex disruption delays motor
 processes but not deliberation about action choices. *Journal of Neurophysiology*,
 1208 122(4), 1566-1577. https://doi.org/10.1152/jn.00163.2019
- Derosiere, G., Thura, D., Cisek, P., & Duque, J. (2021). Trading accuracy for speed over the
 course of a decision. *Journal of Neurophysiology*, *126*(2), 361-372.
- 1211 https://doi.org/10.1152/jn.00038.2021

Derosiere, G., Thura, D., Cisek, P., & Duque, J. (2022). Hasty sensorimotor decisions rely on 1212 1213 an overlap of broad and selective changes in motor activity. PLOS Biology, 20(4), e3001598. https://doi.org/10.1371/journal.pbio.3001598 1214 1215 Desmurget, M., & Turner, R. S. (2010). Motor Sequences and the Basal Ganglia : Kinematics, Not Habits. The Journal of Neuroscience, 30(22), 7685. 1216 1217 https://doi.org/10.1523/JNEUROSCI.0163-10.2010 1218 Ditterich, J. (2006). Evidence for time-variant decision making. European Journal of 1219 Neuroscience, 24(12), 3628-3641. https://doi.org/10.1111/j.1460-9568.2006.05221.x Drugowitsch, J., Moreno-Bote, R., Churchland, A. K., Shadlen, M. N., & Pouget, A. (2012). 1220 1221 The Cost of Accumulating Evidence in Perceptual Decision Making. The Journal of Neuroscience, 32(11), 3612-3628. https://doi.org/10.1523/JNEUROSCI.4010-11.2012 1222 Dudman, J. T., & Krakauer, J. W. (2016). The basal ganglia : From motor commands to the 1223 1224 control of vigor. Current Opinion in Neurobiology, 37, 158-166. 1225 https://doi.org/10.1016/j.conb.2016.02.005 Duque, J., Greenhouse, I., Labruna, L., & Ivry, R. B. (2017). Physiological Markers of Motor 1226 Inhibition during Human Behavior. Trends in Neurosciences, 40(4), 219-236. 1227 1228 https://doi.org/10.1016/j.tins.2017.02.006 Duque, J., Petitjean, C., & Swinnen, S. P. (2016). Effect of Aging on Motor Inhibition during 1229 1230 Action Preparation under Sensory Conflict. Frontiers in Aging Neuroscience, 8. https://www.frontiersin.org/articles/10.3389/fnagi.2016.00322 1231 Eben, C., Billieux, J., & Verbruggen, F. (2020). Clarifying the Role of Negative Emotions in 1232 the Origin and Control of Impulsive Actions. Psychologica Belgica, 60(1), 1-17. 1233 https://doi.org/10.5334/pb.502 1234 Ferrucci, L., Genovesio, A., & Marcos, E. (2021). The importance of urgency in decision 1235 making based on dynamic information. PLOS Computational Biology, 17(10), 1236 1237 e1009455. https://doi.org/10.1371/journal.pcbi.1009455 1238 Fievez, F., Derosiere, G., Verbruggen, F., & Duque, J. (2022). Post-error Slowing Reflects 1239 the Joint Impact of Adaptive and Maladaptive Processes During Decision Making. Frontiers in Human Neuroscience, 16, 864590. 1240 https://doi.org/10.3389/fnhum.2022.864590 1241 Forstmann, B. U., van den Wildenberg, W. P. M., & Ridderinkhof, K. R. (2008). Neural 1242 Mechanisms, Temporal Dynamics, and Individual Differences in Interference Control. 1243 Journal of Cognitive Neuroscience, 20(10), 1854-1865. 1244 https://doi.org/10.1162/jocn.2008.20122 1245 1246 Frank, M. J., Samanta, J., Moustafa, A. A., & Sherman, S. J. (2007). Hold Your Horses : Impulsivity, Deep Brain Stimulation, and Medication in Parkinsonism. Science, 1247 1248 318(5854), 1309-1312. https://doi.org/10.1126/science.1146157 1249 Gold, J. I., & Shadlen, M. N. (2007). The Neural Basis of Decision Making. Annual Review of 1250 Neuroscience, 30(1), 535-574. https://doi.org/10.1146/annurev.neuro.29.051605.113038 1251 Greenhouse, I. (2022). Inhibition for gain modulation in the motor system. Experimental Brain 1252 Research, 240(5), 1295-1302. https://doi.org/10.1007/s00221-022-06351-5 1253 Gross, M. P., & Dobbins, I. G. (2021). Pupil dilation during memory encoding reflects time 1254 pressure rather than depth of processing. Journal of Experimental Psychology: 1255 Learning, Memory, and Cognition, 47(2), 264-281. 1256 https://doi.org/10.1037/xlm0000818 1257 1258 Hanks, T., Kiani, R., & Shadlen, M. N. (2014). A neural mechanism of speed-accuracy tradeoff in macaque area LIP. eLife, 3, e02260. https://doi.org/10.7554/eLife.02260 1259

1260	Herz, D. M., Tan, H., Brittain, JS., Fischer, P., Cheeran, B., Green, A. L., FitzGerald, J.,					
1261	Aziz, T. Z., Ashkan, K., Little, S., Foltynie, T., Limousin, P., Zrinzo, L., Bogacz, R., &					
1262	Brown, P. (2017). Distinct mechanisms mediate speed-accuracy adjustments in					
1263	cortico-subthalamic networks. eLife, 6, e21481. https://doi.org/10.7554/eLife.21481					
1264	Hilz, M. J. (2022). Transcutaneous vagus nerve stimulation—A brief introduction and					
1265	overview. Autonomic Neuroscience: Basic and Clinical, 243.					
1266	https://doi.org/10.1016/j.autneu.2022.103038					
1267	Kaduk, K., Henry, T., Guitton, J., Meunier, M., Thura, D., & Hadi-Bouziane, F. (2023).					
1268	Atomoxetine and reward size equally improve task engagement and perceptual					
1269	decisions but differently affect movement execution. Neuropharmacology, 241,					
1270	109736. https://doi.org/10.1016/j.neuropharm.2023.109736					
1271	Kelly, S. P., Corbett, E. A., & O'Connell, R. G. (2021). Neurocomputational mechanisms of					
1272	prior-informed perceptual decision-making in humans. Nature Human Behaviour,					
1273	5(4), 467-481.					
1274	Kita, K., Du, Y., & Haith, A. M. (2023). Evidence for a common mechanism supporting					
1275	invigoration of action selection and action execution. Journal of neurophysiology,					
1276	130(2), 238–246. https://doi.org/10.1152/jn.00510.2022					
1277	Klein, PA., Petitjean, C., Olivier, E., & Duque, J. (2014). Top-down suppression of					
1278	incompatible motor activations during response selection under conflict. <i>NeuroImage</i> ,					
1279	86, 138-149. https://doi.org/10.1016/j.neuroimage.2013.08.005					
1280	Lawlor, J., Zagala, A., Jamali, S., & Boubenec, Y. (2023). Pupillary dynamics reflect the					
1281	impact of temporal expectation on detection strategy. <i>iScience</i> , 26(2), 106000.					
1282	https://doi.org/10.1016/j.isci.2023.106000					
1283	Lemon, W. C. (1991). Fitness consequences of foraging behaviour in the zebra finch. Nature,					
1284	352(6331), 153-155. https://doi.org/10.1038/352153a0					
1285	Mazzoni, P., Hristova, A., & Krakauer, J. W. (2007). Why Don't We Move Faster?					
1286	Parkinson's Disease, Movement Vigor, and Implicit Motivation. The Journal of					
1287	Neuroscience, 27(27), 7105. https://doi.org/10.1523/JNEUROSCI.0264-07.2007					
1288	McGinley, M. J., David, S. V., & McCormick, D. A. (2015). Cortical Membrane Potential					
1289	Signature of Optimal States for Sensory Signal Detection. Neuron, 87(1), 179-192.					
1290	https://doi.org/10.1016/j.neuron.2015.05.038					
1291	Mosher, C. P., Mamelak, A. N., Malekmohammadi, M., Pouratian, N., & Rutishauser, U.					
1292	(2021). Distinct roles of dorsal and ventral subthalamic neurons in action selection					
1293	and cancellation. <i>Neuron</i> , 109(5), 869-881.e6.					
1294	https://doi.org/10.1016/j.neuron.2020.12.025					
1295	Murphy, P. R., Boonstra, E., & Nieuwenhuis, S. (2016). Global gain modulation generates					
1296	time-dependent urgency during perceptual choice in humans. Nature					
1297	Communications, 7(1), 13526. https://doi.org/10.1038/ncomms13526					
1298	Murphy, P. R., Robertson, I. H., Balsters, J. H., & O'connell, R. G. (2011). Pupillometry and					
1299	P3 index the locus coeruleus-noradrenergic arousal function in humans.					
1300	Psychophysiology, 48(11), 1532-1543. https://doi.org/10.1111/j.1469-					
1301	8986.2011.01226.x					
1302	Niv, Y. (2007). Cost, Benefit, Tonic, Phasic : What Do Response Rates Tell Us about					
1303	Dopamine and Motivation? Annals of the New York Academy of Sciences, 1104(1),					
1304	357-376. https://doi.org/10.1196/annals.1390.018					
1305	O'Connell, R. G., Shadlen, M. N., Wong-Lin, K., & Kelly, S. P. (2018). Bridging Neural and					
1306	Computational Viewpoints on Perceptual Decision-Making. Trends in Neurosciences,					
1307	41(11), 838-852. https://doi.org/10.1016/j.tins.2018.06.005					

- Oldfield, R. C. (1971). The assessment and analysis of handedness : The Edinburgh
 inventory. *Neuropsychologia*, 9(1), 97-113. https://doi.org/10.1016/00283932(71)90067-4
- Park, J., Coddington, L. T., & Dudman, J. T. (2020). Basal Ganglia Circuits for Action
 Specification. *Annual Review of Neuroscience*, *43*(1), 485-507.
 https://doi.org/10.1146/annurev-neuro-070918-050452
- Quoilin, C., Fievez, F., & Duque, J. (2019). Preparatory inhibition : Impact of choice in reaction time tasks. *Neuropsychologia*, *129*, 212-222.
 https://doi.org/10.1016/j.neuropsychologia.2019.04.016
- Ratcliff, R., & Smith, P. L. (2004). A Comparison of Sequential Sampling Models for TwoChoice Reaction Time. *Psychological Review*, *111*(2), 333-367.
 https://doi.org/10.1037/0033-295X.111.2.333
- Ratcliff, R., Smith, P. L., Brown, S. D., & McKoon, G. (2016). Diffusion Decision Model :
 Current Issues and History. *Trends in Cognitive Sciences*, *20*(4), 260-281.
 https://doi.org/10.1016/j.tics.2016.01.007
- 1323 Reppert, T. R., Heitz, R. P., & Schall, J. D. (2023). Neural mechanisms for executive control
 1324 of speed-accuracy trade-off. *Cell Reports*, *42*(11), 113422.
 1325 https://doi.org/10.1016/j.celrep.2023.113422
- Reynaud, A. J., Saleri Lunazzi, C., & Thura, D. (2020). Humans sacrifice decision-making for
 action execution when a demanding control of movement is required. *Journal of Neurophysiology*, *124*(2), 497-509. https://doi.org/10.1152/jn.00220.2020
- \$AHİN, M., & AYBEK, E. (2020). Jamovi : An Easy to Use Statistical Software for the Social
 Scientists. International Journal of Assessment Tools in Education, 6(4), 670-692.
 https://doi.org/10.21449/ijate.661803
- Salamone, J. D., & Correa, M. (2024). The Neurobiology of Activational Aspects of
 Motivation : Exertion of Effort, Effort-Based Decision Making, and the Role of
 Dopamine. *Annual Review of Psychology*, *75*(1), annurev-psych-020223-012208.
 https://doi.org/10.1146/annurev-psych-020223-012208
- Saleri Lunazzi, C., Reynaud, A. J., & Thura, D. (2021). Dissociating the Impact of Movement
 Time and Energy Costs on Decision-Making and Action Initiation in Humans.
 Frontiers in Human Neuroscience, *15.* https://doi.org/10.3389/fnhum.2021.715212
- Schultz, W., Stauffer, W. R., & Lak, A. (2017). The phasic dopamine signal maturing: From
 reward via behavioural activation to formal economic utility. *Current Opinion in Neurobiology*, 43, 139-148. https://doi.org/10.1016/j.conb.2017.03.013
- Shadmehr, R., Huang, H. J., & Ahmed, A. A. (2016). A Representation of Effort in DecisionMaking and Motor Control. *Current Biology*, *26*(14), 1929-1934.
 https://doi.org/10.1016/j.cub.2016.05.065
- Shadmehr, R., Reppert, T. R., Summerside, E. M., Yoon, T., & Ahmed, A. A. (2019).
 Movement Vigor as a Reflection of Subjective Economic Utility. *Trends in Neurosciences*, *42*(5), 323-336. https://doi.org/10.1016/j.tins.2019.02.003
- Spieser, L., Servant, M., Hasbroucq, T., & Burle, B. (2017). Beyond decision ! Motor
 contribution to speed–accuracy trade-off in decision-making. *Psychonomic Bulletin & Review*, *24*(3), 950-956. https://doi.org/10.3758/s13423-016-1172-9
- Steinemann, N. A., O'Connell, R. G., & Kelly, S. P. (2018). Decisions are expedited through
 multiple neural adjustments spanning the sensorimotor hierarchy. *Nature* Our multiple and a state of the sensorimotor hierarchy. *Nature*
- 1353 *Communications*, *9*(1), 3627. https://doi.org/10.1038/s41467-018-06117-0

1354	Steudel-Numbers, K. L., & Wall-Scheffler, C. M. (2009). Optimal running speed and the
1355	evolution of hominin hunting strategies. Journal of Human Evolution, 56(4), 355-360.
1356	https://doi.org/10.1016/j.jhevol.2008.11.002
1357	Thura, D. (2020). Decision urgency invigorates movement in humans. Behavioural Brain
1358	Research, 382, 112477. https://doi.org/10.1016/j.bbr.2020.112477
1359	Thura, D., Beauregard-Racine, J., Fradet, CW., & Cisek, P. (2012). Decision making by
1360	urgency gating : Theory and experimental support. Journal of Neurophysiology,
1361	<i>108</i> (11), 2912-2930. https://doi.org/10.1152/jn.01071.2011
1362	Thura, D., Cabana, JF., Feghaly, A., & Cisek, P. (2022). Integrated neural dynamics of
1363	sensorimotor decisions and actions. PLOS Biology, 20(12), e3001861.
1364	https://doi.org/10.1371/journal.pbio.3001861
1365	Thura, D., & Cisek, P. (2017). The Basal Ganglia Do Not Select Reach Targets but Control
1366	the Urgency of Commitment. <i>Neuron</i> , <i>95</i> (5), 1160-1170.e5.
1367	https://doi.org/10.1016/j.neuron.2017.07.039
1368	Thura, D., Cos, I., Trung, J., & Cisek, P. (2014). Context-Dependent Urgency Influences
1369	Speed–Accuracy Trade-Offs in Decision-Making and Movement Execution. The
1370	Journal of Neuroscience, 34(49), 16442. https://doi.org/10.1523/JNEUROSCI.0162-
1371	14.2014
1372	Vassiliadis, P., Derosiere, G., Grandjean, J., & Duque, J. (2020). Motor training strengthens
1373	corticospinal suppression during movement preparation. Journal of Neurophysiology,
1374	124(6), 1656-1666. https://doi.org/10.1152/jn.00378.2020
1375	Wagenmakers, EJ., Marsman, M., Jamil, T., Ly, A., Verhagen, J., Love, J., Selker, R.,
1376	Gronau, Q. F., Smíra, M., Epskamp, S., Matzke, D., Rouder, J. N., & Morey, R. D.
1377	(2018). Bayesian inference for psychology. Part I: Theoretical advantages and
1378	practical ramifications. <i>Psychonomic Bulletin & Review</i> , 25(1), 35-57.
1379	https://doi.org/10.3758/s13423-017-1343-3
1380	Weinstein, A. M. (2023). Reward, motivation and brain imaging in human healthy participants
1381	– A narrative review. Frontiers in Behavioral Neuroscience, 17, 1123733.
1382	https://doi.org/10.3389/fnbeh.2023.1123733
1383	Wessel, J. R., & Aron, A. R. (2017). On the Globality of Motor Suppression: Unexpected
1384	Events and Their Influence on Benavior and Cognition. <i>Neuron</i> , 93(2), 259-280.
1385	nttps://doi.org/10.1016/j.neuron.2016.12.013
1386	Wilneim, E., Quollin, C., Derosiere, G., Paço, S., Jeanjean, A., & Duque, J. (2022).
1387	Controspinal Suppression Underlying Intact Movement Preparation Fades in
1388	Parkinson's Disease. Movement Disorders, 37(12), 2396-2406.
1389	https://doi.org/10.1002/mds.29214
1390	Yoon, T., Geary, R. B., Anned, A. A., & Shadmenr, R. (2018). Control of movement vigor
1391	Sciences 115(11), https://doi.org/10.1072/ppes.1912070115
1392	Sciences, 175(44). https://doi.org/10.1075/phas.1612979115
1393	Hin, E. A., & Dudman, J. T. (2016). A Proposed Circuit Computation in Basar Ganglia.
1394	history-Dependent Gain. <i>Movement Disorders</i> , 33(3), 704-716.
1395	Tups.//doi.org/10.1002/mas.27321
1390	during lovel walking European Journal of Applied Physiology and Occupational
1200	Developed watching. European Journal of Applied Physiology and Occupational Developed 22(4) 203 306 https://doi.org/10.1007/PE00420227
1200	Thysiology, 33(4), 293-300. IIIIps.//Uol.019/10.1007/DF00430237
1400	Riological Sciences 286(1011) 20101503 https://doi.org/10.1008/rspb.2010.1502
1400	ניין געניאטענעו אוויאטעראא גענידער, גענידיטאט, אווויאטערעטערטערטערטערטעראין גענידער געניגעראטעראין געניארא געני
1401	

1402 Supplementary materials



1403

Figure S1. Movement performance in Experiment 1. Participants successfully escaped the
 ghost (Pacman Success) equally in fast decision blocks (blue bar) and slow decision blocks
 (white bar). Error bars represent SE.

1407

1408





Figure S2. Movement performance in Experiment 2. On average, participants had more difficulty keeping up with the speed imposed in the fast movement blocks (red bars) than in the slow movement blocks (white bars). More precisely, the success rate was lower in fast relative to slow movement blocks for both the first tapping movement (higher percentage of incorrect first movement, left panel) and the following ones in the movement phase (lower percentage of incorrect following movements, right panel). Error bars represent SE. ***p < 0.001.



1417

Figure S3. Typical pupil dilation signal. In order to characterize block-related changes in pupil size during the decision phase, we extracted the peak of pupil dilation (Peak pupil dilation) following the first flexion initiation (Movement initiation) in each trial. This figure shows the

1421 evoked pupil dilation aligned to movement initiation (0) in one subject.



- Figure S4. Control analyses on pupil dilation in Experiment 1 (n=18). As a control analysis, we considered a window of 250 ms before the trial onset to measure tonic pupil dilation. As shown on the left panel, such tonic pupil dilation was similar in fast (blue bar) and slow decision blocks (white bar). Furthermore, block-related changes in tonic dilation (Ranks of Delta tonic) did not correlate significantly with change in Peak pupil dilation (Ranks of Delta phasic), ruling out any pupil bias in our results (right panel).
- 1429
- 1430



1431

1432 Figure S5. Peak pupil data in Experiment 1 (n=18) as a function of urgency at decision

time. Peak pupil dilation was smaller in fast (blue bar) than slow (white bar) decision blocks
(left panel). Consistent with the positive correlation found between pupil dilation and urgency
signal, Peak pupil dilation increased with urgency level in both types of blocks (right panel).
Furthermore, this increase in pupil dilatation with urgency was similar between the two block

1437 types as emphasize by the similar slopes (see inset). Error bars represent SE. ***p < 0.001.

- 1438
- 1439
- 1440
- 1441
- 1442
- 1443
- 1444



1445

Figure S6. Control analyses on behavior in Experiment 1 (n=27). A. Movement duration. 1446 1447 The results showed faster movements in fast decision (blue bar) relative to slow decision (white 1448 bar) blocks (left panel). The duration of movements as a function of decision duration evolved 1449 differently between the two types of blocks (right panel). Although the slopes did not differ from 0 for both fast and slow decision blocks (see inset), the slope for slow decision blocks still 1450 tended to be lower. B. Correlations. Given that deltas were computed by measuring the 1451 difference in duration between fast and slow conditions, the more the subjects showed an 1452 effect of the condition (or coregulation), the more they displayed a negative delta, which 1453 corresponds to a low rank value. So, here you can see that the more participants responded 1454 faster in fast decision blocks compare to slow ones (i.e., the smaller the rank value), the more 1455 they accelerated their movement (i.e., the smaller the rank value) in this block type. Error bars 1456 1457 represent SE. #: t-test against 0 p < 0.025. ***p < 0.001.

1458

1459

1460

- 1462
- 1463



Figure S7. Correlation with UPPS-score in slow decision group of Experiment 2. Given that deltas were computed by measuring the difference in duration between fast and slow conditions, the more the subjects showed an effect of the condition (or tradeoff), the more they displayed a positive delta, which corresponds to a high rank value. Subjects who were more impulsive (higher rank value) tended to show less ability to slow down (lower rank value).

	Fast decision	Slow decision	BF ₁₀	Error %
gender (M/F)	12/15	10/17	0.309	0.008
Age	25.11 ± 3.65	23.81 ± 2.87	0.651	0.008
Urgency	8.52 ± 3.19	8.37 ± 3.20	0.277	0.008
Positive urgency	10.63 ± 2.82	10.56 ± 1.85	0.275	0.008
Lack of Perseverance	7.85 ± 2.52	7.30 ± 2.45	0.361	0.008
Lack of Premeditation	6.70 ± 2.46	7.33 ± 2.45	0.396	0.008
Sensation seeking	11.07 ± 2.05	10.33 ± 3.06	0.430	0.008

Table S1. Demographic description of fast decision and slow decision groups. The table includes the Bayesian independent t-tests for the sex, the age and the five facets of trait impulsivity of the short-UPPS. BF₁₀ grades the strength of evidence for the alternative hypothesis against the null hypothesis. The error percentage (Error %) indicates the numeric robustness of the results, with low values of the Error % corresponding to a greater numerical stability of results. The gender of the participants was transformed into a numerical score to compare the average between the two groups (i.e., 1 for female (F) and 0 for male (M)).

- 1492
- 1493
- 1494
- 1495
- 1496
- 1497
- 1498
- 1499
- 1500
- 1501
- 1502
- 1503
- 1504
- 1505
- 1506

Bin DD	t-value	df	p-value	Cohen's d
1	12.784	55	< 0.001	1.708
2	10.122	55	< 0.001	1.353
3	8.298	55	< 0.001	1.109
4	7.261	55	< 0.001	0.970
5	6.421	55	< 0.001	0.858
6	5.676	55	< 0.001	0.758
7	4.816	55	< 0.001	0.644
8	3.761	55	< 0.001	0.503

1507

Table S2. Paired Student's t-tests of urgency level over decision duration. The critical t-value, the p-value and the Cohen's d as a measure of the effect size are represented for each bin of decision duration (Bin_{DD}). Significant p-value (with a Bonferroni-corrected threshold of .05/8) are highlighted in bold and blue.

1512

1513

Bin DD	t-value	df	p-value	Cohen's d
1	-3.086	17	0.007	-0.727
2	-4.007	17	< 0.001	-0.944
3	-2.352	17	0.031	-0.554
4	-3.561	17	0.002	-0.839
5	-4.408	17	< 0.001	-1.039
6	-3.884	17	0.001	-0.915
7	-3.191	17	0.005	-0.752
8	-5.583	17	< 0.001	-1.316
	1			

1514

Table S3. Paired Student's t-tests of pupil dilation over decision duration. The critical tvalue, the p-value and the Cohen's d as a measure of the effect size are represented for each bin of decision duration (Bin_{DD}). Significant p-value (with a Bonferroni-corrected threshold of .05/8) are highlighted in bold and blue.

1519