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► **To cite this version:**

B. Berret, Gabriel Baud-Bovy. Evidence for a cost of time in the invigoration of isometric reaching movements. 2021. hal-03475795v1

HAL Id: hal-03475795

<https://hal.science/hal-03475795v1>

Preprint submitted on 11 Dec 2021 (v1), last revised 21 Oct 2023 (v3)

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Evidence for a cost of time in the invigoration of isometric reaching movements

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Abstract

How the brain determines the vigor of goal-directed movements is a fundamental question in neuroscience. Recent evidence has suggested that vigor results from a trade-off between a cost related to movement production (cost of movement) and a cost related to our brain's tendency to temporally discount the value of future reward (cost of time). However, whether it is critical to hypothesize a cost of time to explain the vigor of basic reaching movements with intrinsic reward is unclear because the cost of movement may be theoretically sufficient for this purpose. Here we directly address this issue by designing an isometric reaching task in which target-directed movements can be performed accurately and effortlessly in prefixed durations. The cost of time hypothesis predicts that participants should be prone to spend energy to save time even if the task can be accomplished at no movement cost. Accordingly, we found that all participants generated substantial amounts of force to invigorate task accomplishment, especially when the prefixed duration was long enough. Remarkably, the time saved by each participant was linked to their original vigor in the task and predicted by an optimal control model balancing out movement and time costs. Taken together, our results supports the existence of an idiosyncratic, cognitive cost of time that underlies the invigoration of basic isometric reaching movements.

Introduction

Understanding the principles underlying movement invigoration is an important topic in neuroscience given its potential implications for disorders such as Parkinson's disease (Mazzoni et al., 2007). Parkinsonian patients typically suffer from bradykinesia (Berardelli et al., 2001), an overall movement slowness which is related to a dysfunction of the basal ganglia (Turner and Desmurget, 2010; Dudman and Krakauer, 2016; Robbe and Dudman, 2020). Vigor generally characterizes the preferred speed of movement, which has been experimentally quantified through the –idiosyncratic– increase of velocity and duration as a function of distance in simple point-to-point movements. Large differences in vigor were reported across individuals but, remarkably, these differences were consistent between/within sessions or between movement modalities (e.g. head vs hand movements, dominant vs non-dominant reaching or vs walking Reppert et al., 2018; Berret et al., 2018; Labaune et al., 2020). While biomechanical factors may of course play a role, inter-individual differences of vigor were primarily attributed to psycho-economical processes that reflect a trait-like feature of individuality (Shadmehr et al., 2016; Berret et al., 2018; Shadmehr et al., 2019; Carland et al., 2019; Shadmehr and Ahmed, 2020a). The main results point to a cost of time related to the brain's tendency to discount the value of delayed rewards (Shadmehr et al., 2010; Haith et al., 2012; Rigoux and Guigon, 2012; Choi et al., 2014; Berret and Jean, 2016). Assuming that the goal of any movement is to put the system in a more rewarding state (Shadmehr, 2010), moving slowly would decrease the subjective value of reward and would thus be avoided in the control of

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37 goal-directed actions. This principle has been formalized in optimal control theory by using a cost
38 of time that explicitly penalizes the passage of time in sensorimotor control (Hoff, 1994; Berret
39 and Jean, 2016), thereby compensating for the inability of classical trajectory-formation models
40 to account for the duration of self-paced movement (e.g. Flash and Hogan, 1985; Uno et al., 1989;
41 Berret et al., 2011).

42 However, people may also be reluctant to move slowly for alternative reasons (van der Wel et al.,
43 2010; Park et al., 2017; Guigon et al., 2019). Producing a slow movement may be physiologically
44 costly, so a cost of movement alone may be theoretically sufficient to explain our preferred speed. By
45 implication, the cost of time assumed or identified in previous studies could be partly artifactual
46 or only critical to explain the change of vigor in response to modulation of reward or urgency
47 (Takikawa et al., 2002; Reppert et al., 2015; Manohar et al., 2015; Thura, 2020). Objective measures
48 of the cost of movement have shown that metabolic energy expenditure increases at both low and
49 fast speeds, which is a well-known result for walking that seems to be valid for arm reaching as well
50 (Ralston, 1958; Huang and Ahmed, 2012; Shadmehr et al., 2016). Endpoint variance also tends to
51 increase at both fast and slow speeds due to the effects of signal-dependent and constant motor
52 noise unless efficient feedback corrections are triggered by the system (Wang et al., 2016). Effort
53 and variance are two fundamental features of sensorimotor control that are thought to compose
54 the cost of movement (Todorov and Jordan, 2002; Liu and Todorov, 2007; Gaveau et al., 2014,
55 2021; Berret and Jean, 2020). Interestingly, using a cost of movement was sufficient to explain the
56 speed/accuracy trade-off –Fitts’ law– (Harris and Wolpert, 1998; Qian et al., 2013) and why our
57 spontaneous movements are neither too fast nor too slow from mechanistic reasons only (van Beers,
58 2008; Berret et al., 2021). In this case, existing inter-individual differences of vigor could result from
59 discrepancies in the cost of movement represented by people and biomechanical factors. Recently,
60 it has been suggested that the cost of movement could be itself discounted over time (Shadmehr
61 et al., 2016; Summerside et al., 2018) such that movement vigor would essentially reveals “how
62 much we value the things we are moving toward” (Shadmehr and Ahmed, 2020a,b). Obviously,
63 the cost of movement represented by the brain is not yet known exactly (Berret et al., 2011;
64 Summerside and Ahmed, 2021) and this uncertainty is necessarily reflected in the cost of time, the
65 role of which is then particularly unclear for daily actions with intangible rewards. Hence, does
66 the cost of time mainly serve to modulate vigor around some nominal value or does it broadly set
67 movement invigoration?

68 The goal of the present study was to clarify this issue by neutralizing the cost of movement
69 experimentally. To this aim, we designed an isometric pointing task that could be performed
70 accurately and effortlessly in prefixed durations. This is like an airport treadmill that carries
71 travelers to their destination in more or less time depending on whether they stand still or walk
72 on it. Here participants had to control a cursor on a screen via a force applied onto an isometric
73 joystick. A baseline condition was first tested to characterize the behavior of participants in such
74 an isometric reaching task where the reward –if any– is intrinsic, and estimate their original vigor.
75 In a second condition, the cursor had an internal drive such that the task could be accomplished
76 successfully without any participant intervention. If time matters in the control of this isometric
77 reaching task, we predicted that the participants should exert a substantial amount of force onto
78 the joystick to save time, especially when the drive duration is long enough according to the cost
79 of time hypothesis. Furthermore the time savings of each participant should be related to their
80 original vigor in the task if it reflects how they implicitly value task accomplishment. In contrast,
81 if time does not matter and vigor is essentially determined by a cost of movement in this task,
82 participants should favor restful strategies regardless of the drive duration. Indeed, this would be
83 the optimal behavior with respect to the minimization of any cost of movement, whether related
84 to energy, inaccuracy or other factors.

85 **Materials and Methods**

86 **Participants**

87 The experiment included 15 participants (7 females, mean age \pm SD: 27 ± 7). All participants
88 were contacted through a mailing list of persons who volunteer to do experiments at the Italian

89 Institute of Technology and were paid 10 euros for the participation. All participant were naive
90 with respect to the goal of the experiment and signed an informed consent. The experimental
91 protocol was approved by the local ethical committee (C.E.R. Liguria, P.R.063REG2016).

92 **Experimental methods**

93 **Experimental apparatus** The experimental setup comprised an isometric joystick that mea-
94 sured the force applied by the participant on it with a 6-dof force/torque sensor (Mini 45, ATI)
95 and a screen (dimension 19 inch) in front of the participant (distance 65 cm). The joystick was
96 connected to a computer via a digital acquisition card (USB-6211, National Instrument). The force
97 was sampled at 10 kHz and filtered on-line by fitting a linear regression line to the most recent
98 160 samples. A custom C++ program simulated the cursor dynamics at 1 kHz and updated its
99 position on the screen at 60 Hz. The force and system state (position, velocity and external drive)
100 were saved at 60 Hz.

101 **Task** The participant sat in front of the table with the experimental setup and grasped the
102 joystick with the right hand and the elbow bent at 90 degree angle. The participant was instructed
103 to move a cursor toward the target at their preferred velocity. For simplicity the cursor was
104 restricted to move only along the y -axis (bottom-up axis on the screen). The trial was self-started
105 by pushing the space bar on the keyboard. The participant was told to avoid pushing the isometric
106 joystick before the beginning of the trial and the level of force was checked to ensure the participant
107 did not apply a force when starting the trial.

108 The experiment was divided into two sessions that were executed one after the other on the same
109 day.

110 The first experimental session (Session 1) served as a baseline condition from which the vigor and
111 the cost of time of each participant was inferred. It included four movement distances and no
112 assistance was provided (amplitude 0.1, 0.2, 0.3 and 0.4 of screen size [height: 25.5 cm]). The
113 goal of this session was to find out the movement time corresponding to each amplitude, compute
114 nominal vigor scores for each participant and identify the cost of time that would predict these
115 movement times, given a cost of movement based on effort and error (Berret and Jean, 2016).

116 The second session (Session 2) included two different movement distances (0.2 and 0.4). Impor-
117 tantly in this session, an external drive that corresponded to biological movements of different
118 durations ($T_d = 1, 2, 4$ or 6 s) was added to the cursor dynamics.

119 There were 20 repetitions for each condition, thus yielding 80 trials in the first session and 160
120 trials in the second session. The order of presentation of movement amplitudes were randomized in
121 the first session. The conditions in the second session were executed from the slowest to the fastest
122 drive with the amplitude randomized within each condition. In session 2, we used a block-wise
123 design to minimize surprise effects and evaluate behavior when the participant is aware of the
124 current drive applied to the cursor dynamics. Accordingly, each condition in the second session
125 started with two trials that showed the external drive and where the participants was instructed
126 not to touch the isometric joystick.

127 **Cursor Dynamics** The cursor dynamics along the y -axis was as follows:

$$m\ddot{y} = f_s - v\dot{y} \quad (1)$$

128 where $m = 25$ kg and $v = 10$ kg/s are the simulated mass and damping of the virtual system.
129 These values were chosen during preliminary experiments to induce comfortable behaviors and
130 force levels.

131 The force f_s (measured by the force sensor) was the external force applied by the participant on
132 the cursor. Hence, the force applied by the participant directly affected the cursor acceleration.
133 The goal of the task in Session 1 was to move the cursor to a target (1.275 cm width), y_f , from a
134 given home position, y_0 , at the participant's preferred speed.

135 **Choice of external drive** When an external drive was added, the cursor’s dynamics was mod-
 136 ified as:

$$m\ddot{y} = f_d + f_s - v\dot{y} \quad (2)$$

137 where f_d is the external action implemented by an external controller.

138 We noted in preliminary data that participants normally executed this isometric reaching task
 139 using bell-shaped velocity profiles. Therefore, we implemented an external drive as an optimal
 140 feedback control law that allowed to reach the target in a desired duration, T_d , with bell-shaped
 141 velocity profiles.

142 To this aim, we considered a minimum torque change model as it predicts smooth, bell-shaped
 143 velocity profiles (Uno et al., 1989). We noted this optimal control u_d which was the solution of the
 144 optimal control problem described hereafter. We denote by $\mathbf{x} = (y, \dot{y}, f_d)$ the column state vector
 145 and consider the dynamics:

$$\dot{\mathbf{x}} = \mathbf{A}\mathbf{x} + B_d u_d \quad (3)$$

146 where

$$A = \begin{pmatrix} 0 & 1 & 0 \\ 0 & -v/m & 1/m \\ 0 & 0 & 0 \end{pmatrix} \quad \text{and} \quad B_d = \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix}.$$

147 The optimal drive was chosen to move the system from an initial state $\mathbf{x}_0 = (y_f - y_0, 0, 0)$ to a
 148 final state $\mathbf{x}_f = (0, 0, 0)$ in desired time T_d while minimizing the cost:

$$C(u_d) = \mathbf{x}(T_d)^\top Q_f \mathbf{x}(T_d) + \int_0^{T_d} u_d^2(t) dt \quad (4)$$

149 where Q_f is the terminal cost matrix chosen as $Q_f = \text{diag}(6.297 \cdot 10^6, 6.301 \cdot 10^6, 10)$. These
 150 parameters were also determined from preliminary simulations and tests to design an optimal
 151 drive that achieves the task reliably for all durations.

152 Solving this optimal control problem (linear-quadratic in finite horizon) yielded an optimal feedback
 153 control of the form (e.g. Stengel, 1986):

$$u_d(t, \mathbf{x}) = K(t)\mathbf{x} \quad (5)$$

154 where $K(t)$ is the optimal feedback gain defined from $t = 0$ to $t = T_d$. For $t \geq T_d$, we defined
 155 $K(t) = K(T_d)$. Note however that this situation was assumed not to occur in practice as we did
 156 not expect participants to move slower than the duration given by the external drive (it would
 157 be non-optimal with respect to both the cost of movement and the cost of time). We computed
 158 optimal control for drives with duration of T_d equal to 1 s, 2 s, 4 s and 6 s and for distances equal
 159 to $y_f - y_0 = 0.2$ m and 0.4 m. Note that for simplicity we mapped the distances relative to screen
 160 size (see above) to S.I. units in the model for simulations (i.e. using the same numbers).

161 **Coupled cursor dynamics** Once the external drive is defined, we can consider the coupled
 162 dynamics used in the experiment of Session 2. Here the state-space dynamics was as follows:

$$\dot{\mathbf{x}} = \mathbf{A}\mathbf{x} + B_d u_d + B_s f_s \quad (6)$$

163 where $B_s = (0, 1/m, 0)^\top$. The force input of the human participant thus affected directly the
 164 cursor acceleration.

165 Data processing and parameters

166 **Kinematics** The force was the only user input and was filtered on-line (see Experimental Ap-
 167 paratus). Position and velocity being integrated by the dynamic system (Eq. 6) were not filtered
 168 further. For each trial, we identified the beginning of the movement (velocity threshold 0.005 m/s).
 169 The trial and recording finished when the cursor position was inside the target with a velocity below
 170 0.02 m/s. For each trial, we computed the movement duration and the movement amplitude. We

171 also identified if a sub-movement was present (negative velocity) and counted the number of peaks
 172 in the force profile (each force peak corresponds to a period when the absolute of the force is above
 173 1 N for at least 0.1 s). We excluded from the analyses about 13% of the trials because there was
 174 movement reversal, more than five peaks in the force profile or the movement time differed from
 175 the condition average by more than three standard deviation. To compute average trajectories,
 176 single trial trajectories were resampled to have the same number of samples and average duration.

177 **Amount of force** In order to estimate the effort produced by the participant using an objective
 178 measure, we considered the *amount of force* applied during the trial, defined as (Shadmehr et al.,
 179 2016):

$$\int_0^{T_s} |f_s(t)| dt.$$

180 **Vigor scores** In this paper we computed vigor scores using the maximum likelihood approach
 181 described by Reppert et al. (2018) but we used the duration of movements instead of peak velocities.

182 To this end, we first computed the grand mean duration of movements of each amplitude $A_i \in$
 183 $\{0.1, 0.2, 0.3, 0.4\}$ (data of all participants pooled together). These movement durations were then
 184 used to fit the function

$$T_i = g(A_i) = \alpha + \beta A_i, \quad \alpha, \beta \in \mathbb{R}$$

185 The vigor score of each participant $j = 1, \dots, 15$, denoted by vg_j , was finally computed as:

$$\text{vg}_j = \frac{\sum_{i=1}^4 g(A_i)^2}{\sum_{i=1}^4 T_{i,j} g(A_i)}$$

186 where A_i is the movement amplitude and $T_{i,j}$ the individual mean movement time for that ampli-
 187 tude. A score of vigor greater than 1 thus indicates a participant that is more vigorous than the
 188 average of the participants.

189 Statistical analyses

190 We used repeated-measure ANOVAs to analyze movement duration and average force as a function
 191 of movement amplitude and, in Session 2, drive duration. Both factors were coded with polynomial
 192 contrasts to conduct a trend analysis. All statistical analyses were conducted in R (R Core Team,
 193 2019) with *afex* (Singmann et al., 2019) and *emmeans* (Lenth, 2019) packages.

194 Optimal control modelling

195 Here we model the behavior of participants in the second session. We extended the system state
 196 $\mathbf{x} = (y, \dot{y}, f_d)$ to include the human contribution, as $\tilde{\mathbf{x}} = (\mathbf{x}, f_s)$, and considered the following
 197 augmented dynamics:

$$\dot{\tilde{\mathbf{x}}} = \tilde{A}\tilde{\mathbf{x}} + \tilde{B}_d u_d + \tilde{B}_s u_s \quad (7)$$

198 with $\tilde{B}_d = (0, 0, 1, 0)^\top$ and $\tilde{B}_s = (0, 0, 0, 1)^\top$ and

$$\tilde{A} = \begin{pmatrix} 0 & 1 & 0 & 0 \\ 0 & -v/m & 1/m & 1/m \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{pmatrix}. \quad (8)$$

199 where u_d is the optimal drive and u_s is the human motor command. In this model, the motor
 200 command u_s is at the level of force change, which reflects the fact that human force varies smoothly
 201 due to the low-pass filtering property of muscle contraction. The motor optimal drive u_d is also
 202 at the level of torque change and affects the cursor dynamics via f_d . In absence of participant
 203 intervention (i.e., $u_s \equiv 0$), the system is equivalent to Eq. 3 and the cursor moves according to the
 204 previously defined optimal drive.

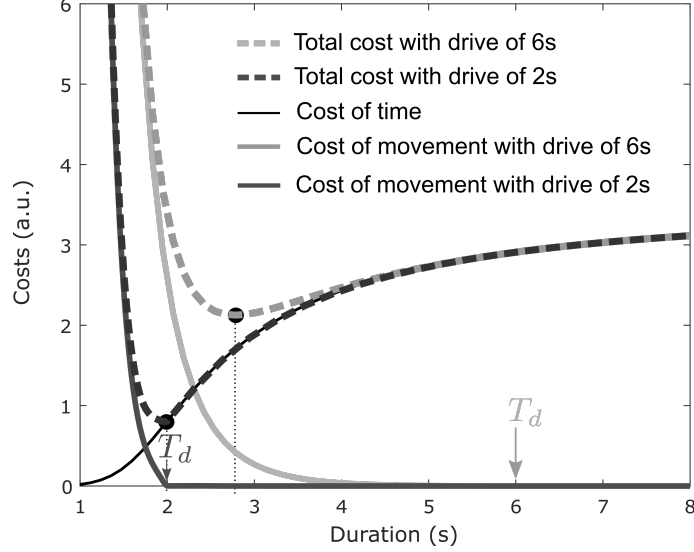


Figure 1: Optimal costs for the task with different drives corresponding to $T_d = 6$ s and $T_d = 2$ s, and a distance of 0.4 m. Cost of movement is zero for times $t \geq T_d$ because u_d already drives the system to the desired target (no effort and no error strategies). Moving faster than duration T_d will require some energy expenditure but allows saving time, which can be a relevant strategy if there is a cost of time. The optimal trade-off between the cost of time and the cost of movement, yielding an optimal movement duration, is indicated by filled circles. When the drive is fast (2 s), the optimal duration remains close to 2 s. However, when the drive is slow (6 s), the optimal duration from the trade-off is around 2.8 s. If there was no drive, the optimal duration would have been 3.1 s in this example.

205 We moreover considered the following cost function:

$$C(u_s) = \mathbf{x}(T_s)^\top Q_f \mathbf{x}(T_s) + \int_0^{T_s} (u_s^2(t) + h(t)) dt. \quad (9)$$

206 where $h(t)$ is the cost of time, T_s is the movement duration, and effort/error terms are modeled as
207 before.

208 The use of the optimal control model involved two steps: (1) an identification step with the data
209 of Session 1; and (2) a prediction step to compare with the data of Session 2.

210 In the identification step, we followed the methodology documented in Berret and Jean (2016) and
211 Berret et al. (2018) to identify the term $h(t)$ for each participant using the data of Session 1 where
212 movement duration T_s is known and external drive is absent ($u_d \equiv 0$ in the above equations).
213 In the prediction step, we solved an optimal control problem in free time to predict movement
214 duration T_s and effort f_s . In this step, external drive u_d is as defined experimentally and the cost
215 of time $h(t)$ is as identified in Session 1, and we assume that the participant minimizes force change
216 (u_s^2) and error (term in Q).

217 The procedure was repeated for each distance of Session 2 (0.2 m and 0.4 m), each T_d (1 s, 2 s, 4 s
218 and 6 s) and each participant (since each participant will have a different cost of time given that
219 their behaviors in Session 1 will differ).

220 This model predicts that participants who behave optimally should trade some physical effort for
221 a gain in time. In other words, if there is a cost of time, they should spend some energy even when
222 there is an external drive that achieves the task by itself. An illustration of the balance between
223 effort and time is provided in Fig. 1. If there is no cost of time, participants should not intervene
224 as it would be the optimal strategy with respect to any cost of movement (for instance effort or
225 accuracy here).

226

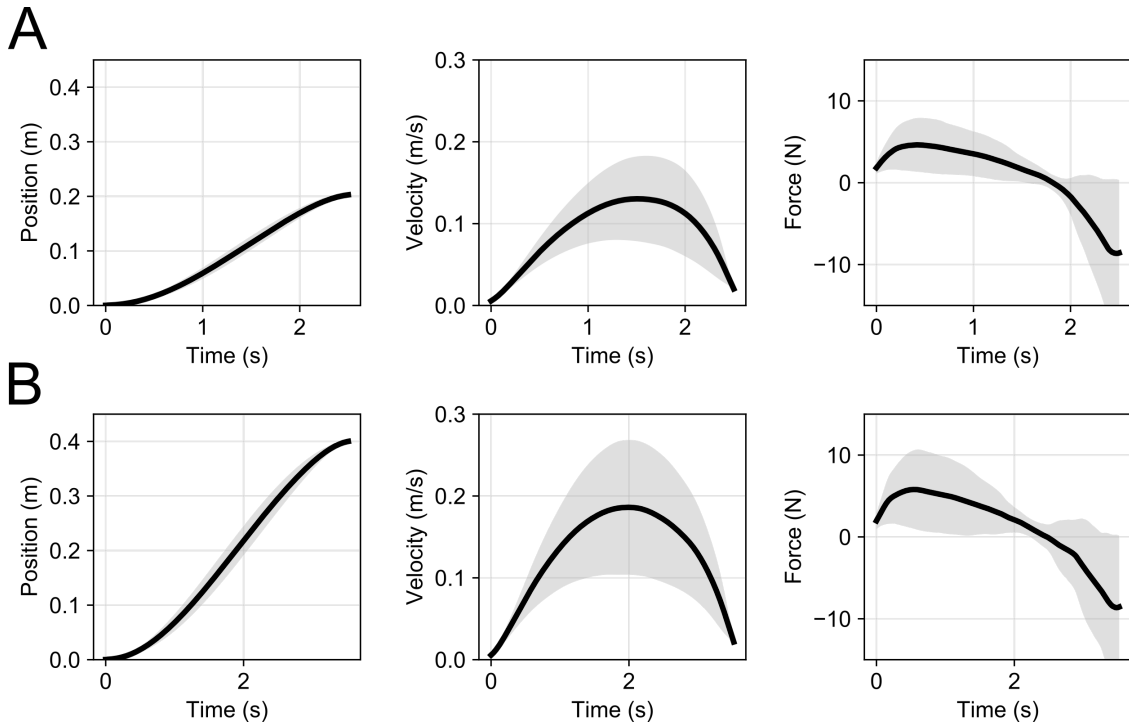


Figure 2: Grand mean trajectories in Session 1. A. Mean displacement, velocity and force for the distance 0.2 m. Thick black lines are means across participants and shaded areas are standard deviations. Trajectories were normalized temporally before computing means and deviations. B. Same information for the distance 0.4 m.

227 Results

228 Experimental results of Session 1 (without drive)

229 **Mean trajectories** Here we describe the average self-paced behavior of the participants in ab-
 230 sence of an external drive. The grand mean trajectories are reported in Figure 2 for the distances
 231 0.2 m (Fig. 2A) and 0.4 m (Fig. 2B) respectively. Velocity profiles are approximately bell-shaped
 232 even though the experimental protocol stopped motion according to some threshold that is visible
 233 at the end of the velocity profiles. Force profiles resemble acceleration profiles and mainly consist
 234 of a positive phase (to accelerate the cursor) and a negative phase to decelerate it. The force
 235 profiles do not return to zero because of the criterion used to detect the end of a trial (see Meth-
 236 ods). Substantial inter-individual differences can be noted for instance on velocity peaks or on the
 237 force used to perform the task. Repeated-measures ANOVA confirmed that movement duration
 238 ($F_{3,42}=85.33$, $\eta_G^2=.39$, $p<.001$) and force ($F_{3,42}=93.93$, $\eta_G^2=.36$, $p<.001$) varied across amplitudes.
 239 A trend analysis revealed that movement time and average force increased linearly with movement
 240 amplitude for the range of values included in the study.

241

242 **Amplitude-duration and amplitude-force relationships** The overall behavior of partici-
 243 pants in terms of movement duration and amount of force are shown in Figure 3 (black filled
 244 circles). As in real point-to-point arm reaching experiments, the duration of movement was found
 245 to increase with amplitude almost linearly, as confirmed by trend analysis (linear: $t_{42}=15.88$,
 246 $p<.001$; quadratic: $t_{42}=-1.95$, $p=.06$). Movements of distance corresponding to 0.2 m and 0.4 m
 247 were performed in about 2.5 s and 3.5 s respectively. The amount of force also increased with
 248 amplitude in a similar way (linear: $t_{42}=16.76$, $p<.001$; quadratic: $t_{42}=-0.92$, $p=0.36$). The grand
 249 mean amount of force was about 7 N for the distance 0.2 m and 11 N for the distance 0.4 m. Again,
 250 a relatively large inter-individual variability was visible here and we thus focus on some individual

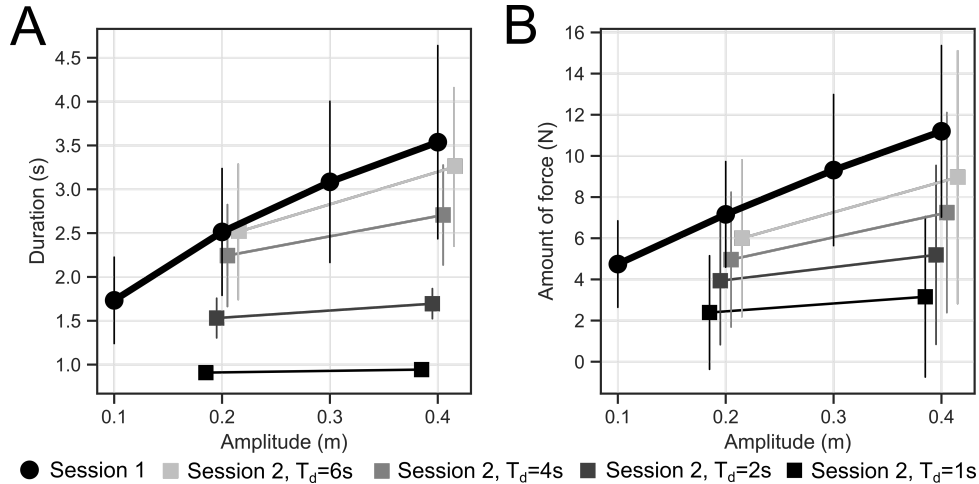


Figure 3: Mean behavior across participants as a function of distance. A. Amplitude-duration relationships in Sessions 1 and 2. Filled circles are data from Session 1 for the 4 tested amplitudes. Grey-colored filled squares are data from Session 2 for the 4 drives and the 2 amplitudes tested. Vertical bars represent standard deviations in all cases. B. Same information for the amplitude-amount of force relationships.

251 performance scores in the following.

252

253 **Individual movement vigor scores and costs of time** The relationship between amplitude
 254 and duration for each individual is reported in Figure 4A. A color code is used to track each indi-
 255 vidual throughout the study. Linear regressions confirmed that duration increased with movement
 256 amplitude in an approximately affine way for every participant ($R^2 = 0.97 \pm 0.03$ across partic-
 257 ipants). From these relationships, it was possible to compute vigor scores and sort individuals
 258 according to these scores (Fig. 4B) (see Methods).

259

260 Furthermore, the same relationships allowed us to identify the cost of time for each participant
 261 (see also Methods). The resultant costs of time are depicted in Figure 4C. As expected since
 262 both measures are derived from the same data, there is a strong correlation between the vigor of
 263 participants and the magnitude of their cost of time (Fig. 4D). Typically, the faster participants in
 264 Session 1 (i.e. with larger vigor scores) penalized time more steeply (i.e. increased more quickly,
 265 and to a higher asymptotic value, their time costs).

266 Experimental and simulation results of Session 2 (with drive)

267 We now consider the experimental data of Session 2 where the external drive allows, in theory,
 268 the participant to complete the task without any muscular force. Figure 5 depicts the grand mean
 269 behavior across participants for two different drives (2 s and 6 s) and the two distances tested in
 270 this Session (0.2 m in panels A-C and 0.4 m in panels D-F). These two distances were illustrated for
 271 Session 1 in Fig. 2 for comparison. Black/grey traces show the experimental data and red/purple
 272 traces show the simulated data. The simulations relied on the costs of time identified from the
 273 data of Session 1 (one cost of time per participant) and the free-time optimal control simulations
 274 minimizing a trade-off between the cost of movement and the individual-based cost of time (which
 275 explains why simulated data also vary across participants). Velocity profiles are bell-shaped as in
 276 the first Session. Force profiles appear more irregular but they still present a positive and negative
 277 peaks that corresponds to an acceleration and deceleration of the cursor, even though the presence
 278 of the drive may both accelerate and decelerate the cursor on its own. The figure shows that
 279 participants used some force to save time, thus achieving the task in less than 3.5 s when the drive

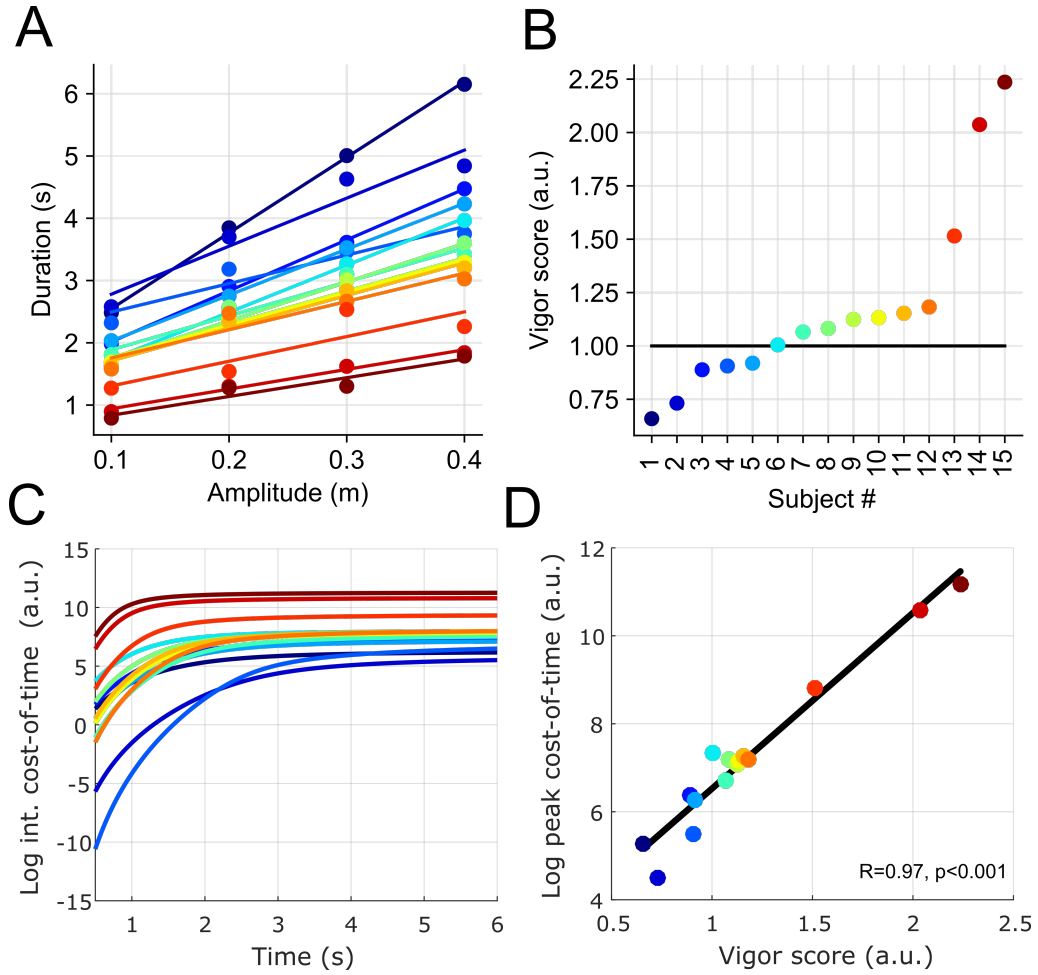


Figure 4: Individual vigor scores. A. Amplitude-duration relationships in Session 1. Each color is the data of one participant. Linear regression lines are displayed. The cost of time was inferred from these individual-level relationships. B. Corresponding vigor scores allowing to sort individuals from the slowest to the fastest in the isometric reaching task of Session 1. The horizontal black line corresponds to a reference vigor score of 1. C. Logarithm of the costs of time identified for each participant, i.e. $\log(\int_0^T h(t)dt)$. D. Correlation between the vigor scores and the logarithm of the peak derivative of the costs of time (i.e. the maximal value of $h(t)$).

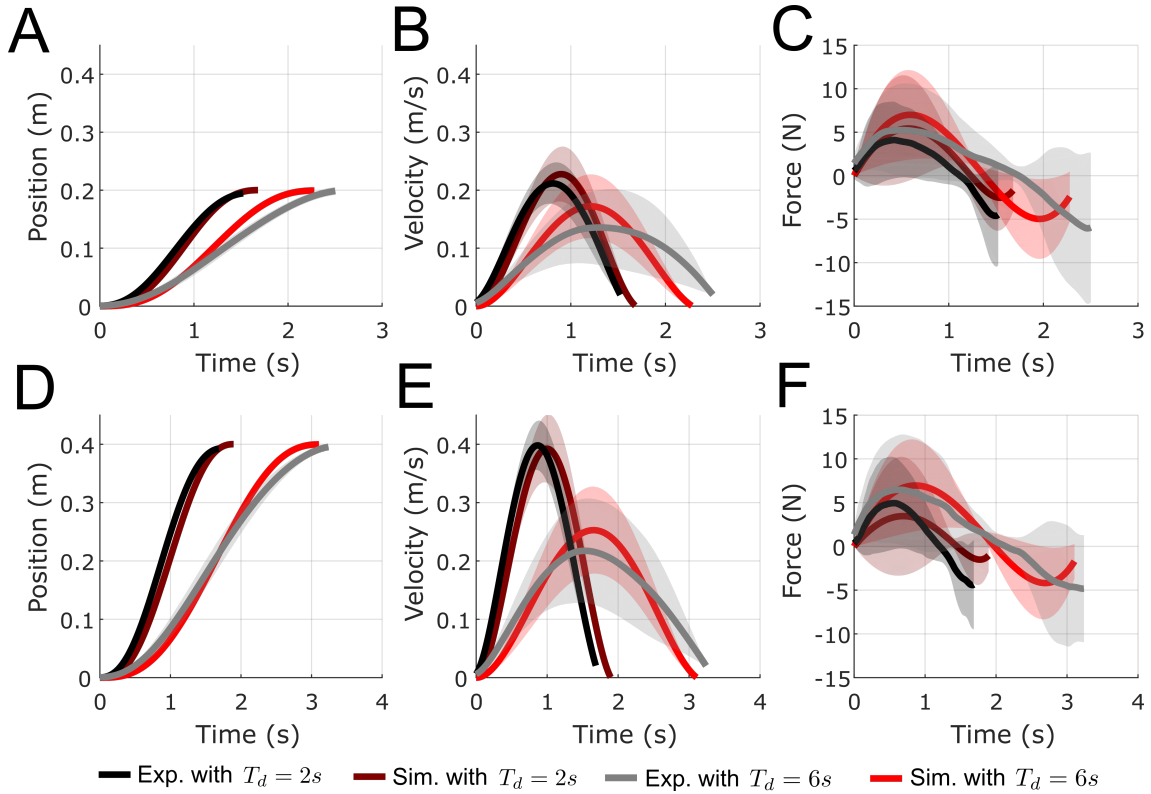


Figure 5: Experimental and simulated trajectories in presence of the drive. A. Cursor displacements in the experiments (black/grey) and simulations (purple/red), for two different drive durations (2 s and 6 s), for the distance 0.2 m. Mean trajectories across participants are reported with standard deviations as shaded areas. B-C. Same information for the velocity and force respectively. D-F. Same information but for the distance 0.4 m.

280 corresponded to a 6 s movement duration for example. Noticeably, participants still used some
 281 force on average even when the drive was stronger and would lead to a 2 s long movement on its
 282 own.

283 Mean movement duration and amounts of force across participants are reported in Figure 3 (filled
 284 squares). As expected, the performance became closer to that of Session 1 as the drive duration
 285 increased. Average movement duration increased with drive duration ($F_{3,42}=69.25$, $\eta_G^2=.68$,
 286 $p<.001$) and amplitude ($F_{1,14}=393.36$, $\eta_G^2=.10$, $p<.001$). The statistically significant interaction
 287 ($F_{3,42}=63.47$, $\eta_G^2=.065$, $p<.001$) reflected a steeper increase of the movement duration with drive
 288 duration for large movement than for small movements (contrast between linear trends: $t_{42}=16.62$,
 289 $p<.001$). A similar analysis of average force revealed the same trends. Average amount of force
 290 also increased with drive duration ($F_{3,42}=17.27$, $\eta_G^2=0.15$, $p<.001$) and amplitude ($F_{1,14}=19.56$,
 291 $p<0.001$). The statistically significant interaction ($F_{3,42}=21.33$, $\eta_G^2=0.01$, $p<.001$) reflected a
 292 steeper increase of the average force with drive duration for large movement than for small move-
 293 ments (contrast between linear trends: $t_{42}=6.02$, $p<.001$).

294

295 In Figure 6, we depict mean movement durations chosen by participants in Session 2 and compare
 296 them to drive durations (black identity line –indicating the optimal duration if only a cost of
 297 movement is minimized–) and model predictions (red trace and shaded area). The overall behavior
 298 was as follows: movement duration increased with the duration of the drive and tended to plateau
 299 near the movement duration obtained in Session 1 for slow drives. Indeed, the movement duration
 300 of participants for a drive of 6 s was closed to the duration obtained in Session 1 (dotted line in
 301 Fig. 6). Noticeably, the model replicated quite well this average behavior. An optimal trade-off

302 between movement and time costs thus leads to this evolution of movement duration with respect
303 to drive duration for each distance.

304

305 Next, we analyzed the force that participants were prone to exert to save a given amount of
306 time. We thus focused on the relationship between the gain of time and the amount of force used
307 by the participants to complete the task, the gain of time being defined as the drive duration
308 minus the actual duration. We found that all the participants tended to increase the amount
309 of force to save more time across conditions (Fig. 7). The model replicated this trend quite well
310 although it generally tended to overestimate the amount of force necessary to save a given amount of
311 time. Important inter-individual differences could also be noted. For instance, to save one second,
312 participants could use quite different amounts of force (e.g. less than 5 N for the participant with
313 the lowest vigor to more than 10 N for the participant with the higher vigor).

314

315 Finally, we investigated if there was any relationship between the vigor of participants in Session 1
316 and their behavior in Session 2 (Fig. 4). Remarkably, we found that the more vigorous participants
317 in Session 1 were indeed the ones saving more time in Session 2 (high correlations with $r > 0.90$ for
318 both tested distances, $N=15$ participants). These participants were also the ones using a greater
319 amount of force (correlation coefficients between vigor and average amount of force $r > 0.90$ –not
320 depicted–). In summary, vigorous participants spent more energy to save more time.

321

322 Discussion

323 Recent studies have suggested that the vigor of movement results from a trade-off between a cost
324 related to movement production and a cost related to the passage of time. However, whether a cost
325 of time underlies the vigor of simple reaching movements remains unclear as a cost of movement
326 could be theoretically sufficient to explain our preferred speed on average. This cost of time could
327 mainly serve to modulate our speed around a reference value according to the urgency or reward
328 of the task. To disambiguate this question, we designed an isometric pointing task that makes
329 distinct predictions depending on whether a cost of movement or a cost of time is prevalent. In
330 some conditions, a drive moved the cursor to the target with a certain duration such that the task
331 could be accomplished accurately and effortlessly with no participant intervention. Despite this
332 self-completion of the task, the participants exerted all the more force the slower the movement
333 of the cursor was and the higher their original vigor in the task was, in agreement with optimal
334 control simulations assuming a trade-off between time and effort. These findings are compatible
335 with the existence of an idiosyncratic, cognitive cost of time underlying the invigoration of basic
336 isometric reaching movements.

337 Producing a movement inevitably entails a motor cost that can be translated into tangible variables
338 such as metabolic energy, effort, smoothness, error or variance. The identification of the cost that
339 best reproduces human trajectories has attracted a lot of attention in optimal control theory
340 (see Engelbrecht, 2001; Todorov, 2004; Berret et al., 2019 for reviews) but it has proven difficult to
341 unequivocally identify the cost of movement because of its potential compositeness and subjectivity
342 (Berret et al., 2011; Summerside and Ahmed, 2021). The design of our task circumvents this issue
343 by creating a condition in which the task accomplishes by itself, thereby neutralizing the cost of
344 movement for specific motion durations. Despite this opportunity to perform the task accurately
345 and effortlessly, our participants systematically exerted some force onto the joystick to achieve
346 the task more quickly. They clearly favored saving time over saving energy in this task. Yet,
347 when the drive was present, it was always optimal to remain inactive with respect to any cost of
348 movement. This suggests that slow movements are generally avoided, not specifically because they
349 may incur a large cost related to movement execution but mostly because they last long (van der
350 Wel et al., 2010). This predominance of movement duration over energy expenditure was also
351 found in a perceptual decision-making task at movement initiation (Lunazzi et al., 2021). Morel

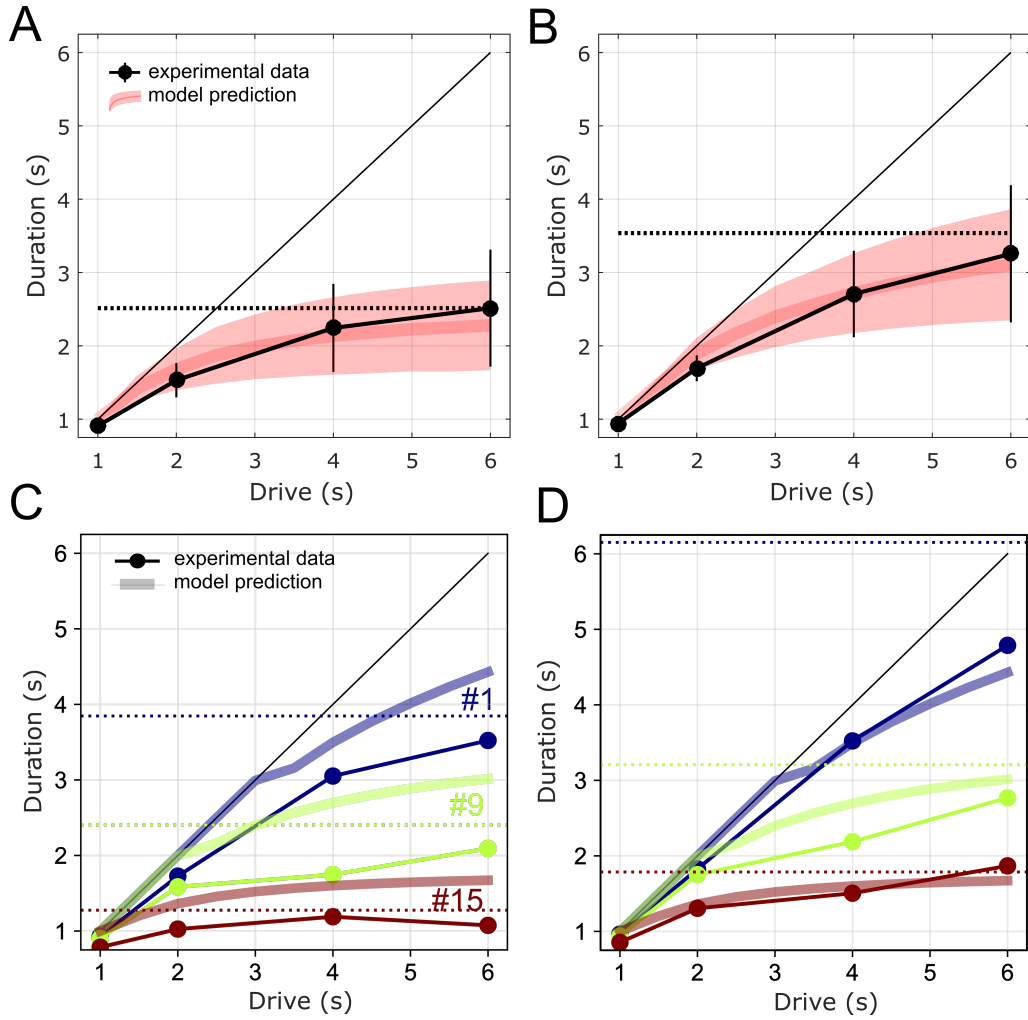


Figure 6: Movement duration with respect to drive duration in Session 2. A. Mean experimental and simulated data for distance 0.2m. Black markers and traces are experimental data. Mean and standard deviations across participants are reported. Red traces and shaded areas are model predictions (also mean and standard deviations across participants). The horizontal dotted line correspond to the mean duration measured in Session 1 for that distance. The identity line corresponds to the drive duration, which would be the optimal duration if only a cost of movement is minimized. B. Same information for distance 0.4 m. C-D. Same information for three participants with high, medium and low vigor respectively.

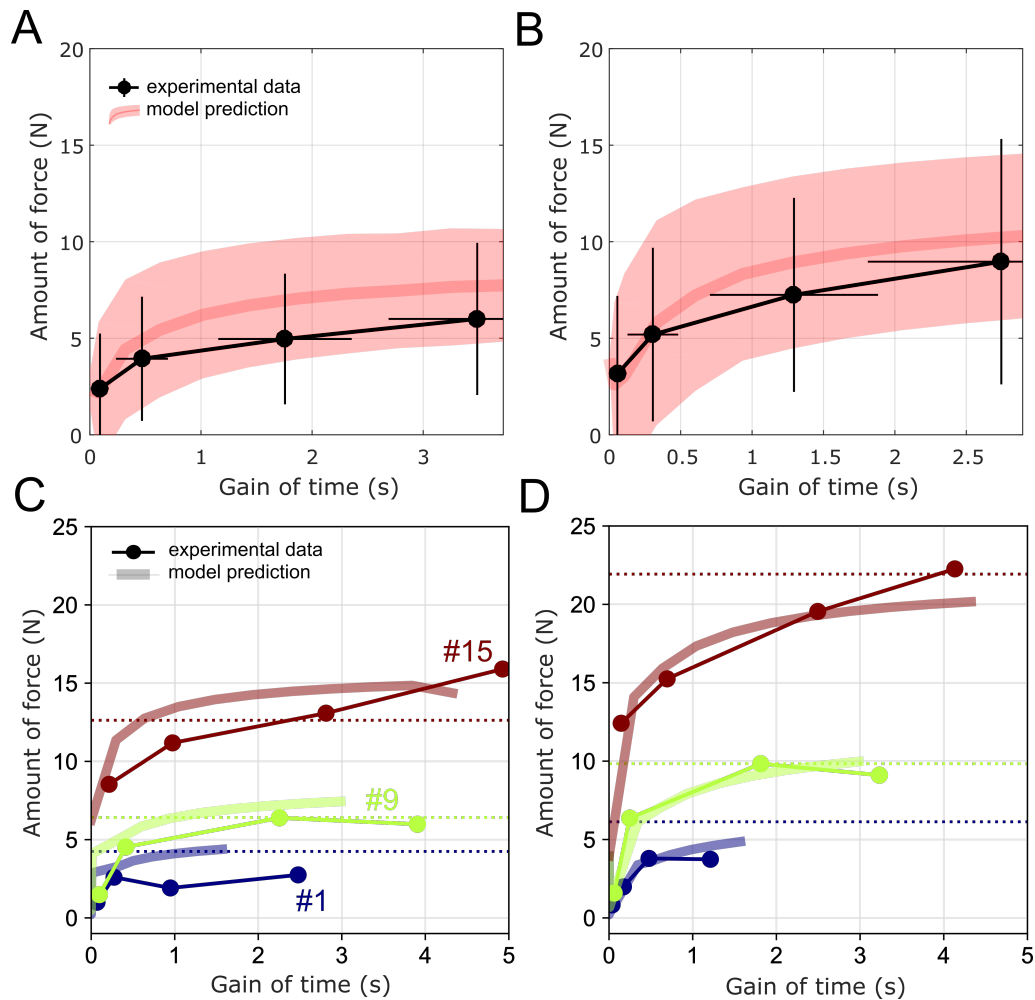


Figure 7: Relationship between gains of time and amount of forces used in Session 2. A. Mean experimental and simulated data for distance 0.2m. Black markers and traces are experimental data. The black filled circles correspond to the drives in the following order: 1s, 2s, 4s and 6s respectively. Mean and standard deviations were calculated across participants. Red traces and shaded areas are model predictions (also mean and standard deviations across participants). The horizontal dotted line correspond to the mean amount of force measured in Session 1 for that distance. B. Same information for distance 0.4 m. C-D. Same information for three participants with high, medium and low vigor respectively.

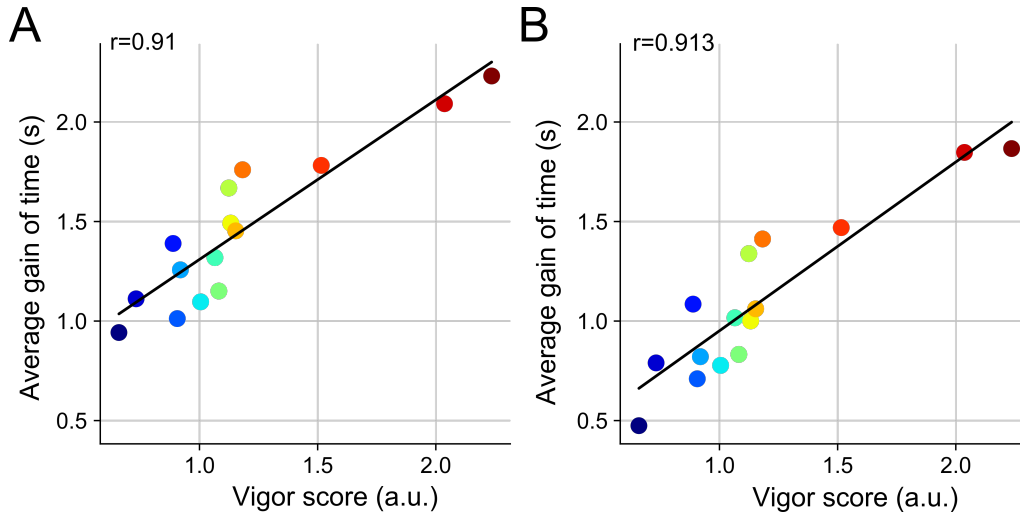


Figure 8: Relationship between vigor scores as measured in Session 1 and average gains of time in Session 2. Same color code than in Figure 4. Each dot is a participant. A. Distance 0.2 m. B. Distance 0.4 m.

352 et al. (2017) have shown that duration is indeed a key factor that makes people judge a reaching
 353 movement as “effortful”, and that this judgement does not seem to be based on objective measures
 354 such as metabolic energy. Here, it was clear that our participants did not minimize isometric force
 355 production alone, which suggests that the passage of time may contribute to action selection *per*
 356 *se* and perhaps to a subjective representation of effort. It has been proposed that the cost of time
 357 mainly expresses a subjective temporal discounting of reward within the brain, which could explain
 358 why the participant achieved the task more quickly than what is prescribed by the drive. This
 359 cost of time has been reviewed in several recent articles (Shadmehr et al., 2019; Carland et al.,
 360 2019) and a monograph (Shadmehr and Ahmed, 2020a), and might even reflect general personality
 361 traits (Choi et al., 2014; Berret et al., 2018). Hence the most vigorous participants should be the
 362 steepest temporal discounters and/or the ones who attribute the greatest subjective value to task
 363 accomplishment (Reppert et al., 2015; Yoon et al., 2020; Shadmehr and Ahmed, 2020a). This
 364 prediction agreed well with our findings that the most vigorous participants (as sorted from a
 365 baseline experiment) were the ones spending more energy to save a given amount of time. In our
 366 case, the cost of time may also capture an attentional cost related to the fact that participants
 367 were observing the motion of the cursor on the screen even when exerting no force, or just that
 368 they were engaged in the task. Since these higher-level costs are not strictly related to movement
 369 production processes, they are excluded from our definition of the cost of movement but can be
 370 integrated into a cognitive cost of time.

371 Although we mainly interpreted our results within the cost of time theory, it could be argued
 372 that participants just preferred to be active in the task. In this case, participants would also
 373 have preferred to move the cursor by themselves rather than to passively look at it. Assessing
 374 passivity from an amount of force lower than 0.15 N, a total of 3, 2, 1 and 0 participants passively
 375 executed the task for the drive durations 1 s, 2 s, 4 s and 6 s respectively (for both distances). For
 376 instance, one participant (#6) remained passive for drive durations ≤ 4 s but suddenly became
 377 active when the drive lasted 6 s. However, participants were generally active even for the smaller
 378 drive durations. The critical observation is that participants did not exert forces onto the joystick
 379 arbitrarily or just by habituation (e.g. using a fixed amount of force or fixed gain of time in
 380 the task). In contrast, they saved time and exerted force in an idiosyncratic manner that was
 381 closely linked to their the original vigor in the task and that depended on the drive duration as
 382 predicted by an optimal control model based on their identified cost of time (which were obtained
 383 before the drive was introduced). Accordingly, highly vigorous participants were highly active in
 384 most conditions even for the 1 s or 2 s drives. These participants were clearly prone to spend a
 385 substantial effort to save a small amount of time. This may seem surprising but it fits well with

386 the theory of vigor (Shadmehr and Ahmed, 2020a) and a putative link with personality traits
387 like impulsivity or boredom proneness (Choi et al., 2014; Berret et al., 2018). Weakly vigorous
388 participants were also active in most conditions but produced much lower amounts of force in the
389 task, that is, they were also inclined to save time but much less than participants with high vigor
390 scores. These observations show that participants did not simply prefer to be active with arbitrary
391 levels of force and durations, nor did they try to replicate their baseline behaviour regardless of
392 the duration of the drive. Instead, they energize the movement according to both their own vigor
393 (or implicit motivation, Mazzoni et al., 2007) and the characteristics of the drive in agreement
394 with an optimality principle minimizing a trade-off between a cost of movement and a cost of time.
395 Another argument may be that the passage of time is subjectively faster when one is actively
396 moving. The literature indeed suggests that the perception of time could be itself modulated
397 by our ongoing voluntary actions (Eagleman, 2008; Merchant and Yarrow, 2016). For instance,
398 saccadic eye movements seem to produce a time compression (Morrone et al., 2005), an observation
399 which has been generalized to hand reaching movement and isometric force production (Tomassini
400 et al., 2014). In the latter study, participants had to judge the time interval between tactile taps
401 and time intervals defined by tactile stimuli were perceived as shorter when hand movements were
402 prepared and executed. This psychophysical phenomenon is not incompatible with the hypothesis
403 of a cognitive cost of time. Indeed, to either save true time or its subjective perception, it would
404 have been worthwhile for the participants to energize task’s achievement. Interestingly, the link
405 between impulsivity and the sense of time have been reviewed in (Wittmann and Paulus, 2008)
406 and it was suggested that “[impulsive] individuals are more likely to experience a slowing down
407 of time during situations in which they are not able to act on their impulsive urges, for example
408 when one has to wait for a delayed reward and is confronted with the passage of time”.

409 To draw the present conclusions we relied on an isometric reaching task. The advantage of this
410 task is that it allows resolving a number of issues that would occur with real movements. First,
411 it removes the problem of dealing with participant-dependent or poorly known biomechanical
412 limb parameters for different participants (inertia, centers of mass etc.). This lack of knowledge is
413 typically problematic when estimating an objective cost of movement using musculoskeletal models.
414 Here every participant controlled the same virtual point mass. Therefore, only the endpoint force
415 was used to move the cursor, which allowed for a simpler definition of the movement cost in this
416 task even though different choices were still possible. Here we used the amount of force as in
417 (Shadmehr et al., 2016) (i.e. force-time integral) to estimate energy expenditure as objectively
418 as possible from our experimental data. One limitation could be that we did not consider the
419 metabolic cost of sitting with the arm still on the handle. However, this constant cost is unlikely
420 to explain the motor decisions of the participants in our task as it is not related to movement
421 but posture (see also Summerside and Ahmed, 2021 for a similar conclusion in a study estimating
422 metabolic cost using expired gas analysis). Differences between participants could still arise from
423 differences in their force production capacities, although this would not disprove the evidence for
424 a cost of time in this task because the cost of movement was neutralized in any case with the
425 drive. Second, isometric reaching simplifies the implementation of the drive because there is no
426 physical interaction between the moving cursor and the participant. It should be possible to create
427 similar experimental tasks with real movements. For instance, generalization of this task could
428 involve a long treadmill for walking or an exoskeleton/manipulandum for providing participants
429 with assistive control laws at different speeds. Another limitation of our study is that an isometric
430 reaching task may not be very ecological. Yet, isometric reaching tasks have been used successfully
431 in the past to explore the neural control of movement, in particular trajectory planning, motor
432 adaptation, muscle synergies and optimal control (Ghez et al., 1997; de Rugy et al., 2012, 2013;
433 Berger et al., 2013; Rotella et al., 2013). Hence, it has proven to be an interesting paradigm that
434 can provide relevant insights about the control of goal-directed actions. Choosing between time
435 and effort is indeed a commonly encountered situation in daily life (e.g. the airport’s treadmill
436 example) and it is possible that the principles of such in-lab experiments will generalize to more
437 ecological tasks such as choosing between taking the car or go by foot, take an escalator or climb
438 the stairs, use his/her slow neuro-prosthetic arm or healthy arm and so on. Future work will aim at
439 using a motorized upper-limb exoskeleton to assist the movements of participants and test whether
440 similar principles apply when muscles produce work and a real movement of the limb occurs.

⁴⁴¹ **Acknowledgments**

⁴⁴² We thank Nicolò Balzarotti for his help during the data acquisition. We also thank Dorian Verdel
⁴⁴³ and Jérémie Gaveau for useful comments on earlier versions of the manuscript.

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