Decision-Making Under Effortful Constraints: The Impact of Acute High-Intensity Activity on Cognitive Processes

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Abstract

This study investigates the acute impact of high-intensity activity on decision-making processes, using computational modeling to assess changes induced during and after an effortful activity. Participants completed a perceptual decision-making task at rest, both before and after a series of eight 5-minute cycling bouts (totaling 47 minutes) at 86 ± 7% of their maximum heart rate (HRmax). They also performed the decision-making task in a dual-task condition (cognitive and physical effort) at various time points during cycling, specifically during six of the eight 5-minute bouts. Cognitive processes were assessed by fitting a drift diffusion model (DDM) to accuracy and reaction time data, allowing us to assess changes in perceptual discrimination, decision bias, encoding of relevant information, and decision execution. Findings suggest an improvement in cognitive performance at rest immediately after the effortful activity, with significant changes in DDM parameters indicating enhanced perceptual discrimination and more efficient non-decisional processing compared to pre-activity. During the effortful activity, we observed a decrease in decision thresholds over the course of the demanding dual-task, reflecting reduced caution, alongside a dynamic adjustment in non-decisional time. These findings provide new insights into how sustained high-intensity activity modulates decision-making mechanisms, contributing to our understanding of effort's impact on cognitive processing.

Introduction

April 15, 2019. Notre-Dame is ablaze. After a strenuous climb, during which a firefighter analyzes and interprets the situation, she finally reaches the top of the tower. Now, she must decide which side of the raging fire to attack first. Is her decision-making affected by sustained physical and mental effort? And if so, which specific cognitive processes are altered during and after this demanding, effortful activity?

It is well established that acute moderate-intensity activity can enhance cognitive performance across various cognitive tasks, including memory, vigilance, and conflict resolution (e.g., Morris, 2021; Pontifex et al., 2019). However, recent narrative reviews have underscored the well-established effects of moderate-intensity aerobic activity on cognitive performance, contrasting with the less clarified impacts of high-intensity aerobic activity (Sudo, Costello, McMorris & Ando, 2022; Zheng et al., 2021; Pontifex et al., 2019). Despite theoretical expectations, the literature regarding the effects of high-intensity activity on cognitive performance is inconclusive and contradictory (McMorris, 2021; Moreau and Chou, 2019). While some studies support the notion of impaired cognitive performance following high-intensity activity, others suggest no significant effects or even improvements. This ambiguity highlights the complexity of the relationship between high-intensity effortful activity and cognitive function, indicating that further research is needed to fully understand these effects. The emphasis on moderate-intensity activity, primarily driven by methodological considerations, has

left a gap in our comprehension of the interaction between effortful activity and cognitive performance, especially when physiological demands are substantial.

The impact of high-intensity activity, defined as physiological demand exceeding 80% maximal oxygen uptake (McMorris et al., 2016), or equivalent [e.g., exceeding 80% maximal heart rate (HRmax)], warrants deeper investigation. This is particularly crucial because it is associated with more pronounced cellular and molecular changes than conventional aerobic activity (Herold et al., 2019). Consequently, its influence on cognitive processes, likely mediated by specific peripheral biomarkers associated with high-intensity effortful activity, such as circulating lactate (Hashimoto et al., 2021), blood glucose, circulating cortisol levels, or neurotrophic factors (Singh & Staines, 2015), may differ from the commonly reported findings in existing literature. These systemic physiological adaptations could have widespread effects on the organism, potentially altering cognitive functioning. For instance, they may enhance motor cortex sensitivity to upstream influences, increase sensory sensitivity (facilitating stimulus encoding), elevate arousal levels (accelerating processing speed), and modulate corticospinal excitability (promoting response execution).

Quantifying the influence of effortful activity on cognitive processes poses a challenge because these processes cannot be directly observed. The cognitive computational approach provides a way to tackle this issue. It offers theoretically grounded models, whose parameters represent latent cognitive processes and can be inferred from behavioral data. In this study, we relied on the Drift Diffusion Model (DDM, Ratcliff, 1978) to decipher the impact of high-

intensity intermittent exercise on cognitive processes involved in a perceptual decision-making task. This model has proven to be particularly fruitful (Ratcliff et al., 2016). It belongs to the wide class of Evidence Accumulation Models (EAM, Bogacz et al., 2006), which postulate that decisions result from the continuous accumulation of a stochastic evidence until a given amount of evidence is attained. The basic DDM contains four parameters, each related to a different cognitive process: the starting point of the accumulation process (z), which represents the bias of the decision; the drift rate of the accumulation process (v), which depends on the difficulty of the task or on the subject's perceptual ability; the distance between the bounds corresponding to each response (a), which represent the subject's cautiousness (the larger a, the more accurate and slower the responses); and a non-decision time (Ter), that encompass the encoding of relevant information and the decision execution processes. Specifically, participants performed a random dot motion task, a task for which the DDM consistently offers excellent explanations for behavioral data, both before, during, and after engaging in an effortful high-intensity activity consisting in eight 5-minutes bouts cycling exceeding 80% HRmax. Cognitive processes were assessed by determining the best-fitting parameters of a model based on behavioral data (accuracy and reaction times).

Materials and methods

Participants

Nineteen young adults (one woman, age range: 18–34; mean age: 25 years) voluntarily participated in the experiment. All participants were healthy and practiced regular physical

activities (peak oxygen uptake: 55 ± 8 mL kg−1 min−1; maximal heart rate: 184 ± 9 bpm). All participants were fully informed about the study and signed a written informed consent before inclusion. The study was approved by the Ethics Committee for Research in Science and Technology of Physical Sports Activities (IRB00012476-2022-21-01-148).

Random dot motion task (RDK)

We used a perceptual decision-making task, the random dot motion task (RDK), for which the DDM has consistently provided excellent accounts of behavioral data. The experiment was programmed in Python, utilizing components of the PsychoPy toolbox (Peirce et al., 2019), and was executed on a PC computer operating natively on Windows 10 with a 19.5-inch screen. Participant responses were recorded using two buttons (one for each hand).

The task requires participants to determine the global direction of a random dot kinematogram featuring a proportion of dots moving coherently in the left or right signal direction. Each trial started with the presentation of the random dot motion stimulus, which remained on the screen until the participant responded. A response time deadline was set to 5 s. The interval between the response to the stimulus and the next trial was 1.5 s. The coherence parameter (proportion of dots moving in the same direction) was set for each participant at the beginning of the experiment according to a 2 up and 1 down staircase method lasting 30 trials. White dots were presented within a virtual 12.6° circular aperture centered on a 24.8° 3 13.9° black field. Each dot was a 4 x 4 pixel (0.05° square), moving at a speed of 8°/s. Dot density was

fixed at 16.7 dots/deg2/s. Random dot motion was controlled by a white noise algorithm (Pilly & Seitz, 2009).

Procedure

Participants made three separate visits to the laboratory, each spaced at least 48 hours apart: a characterization session, a familiarization session, and the experimental session. Participants were positioned on an upright cycle ergometer (Lode Excalibur Sport, Groningen, The Netherlands), equipped with two thumb response buttons on the right and left handle grips. A computer screen was positioned at eye level, approximately 1 meter in front of the participant.

The preliminary session was conducted to individually adjust the difficulty of the cognitive task, assess V̇O2max, and determine ventilatory thresholds (Wasserman, 2012) (see Table 1 for details). Participants were seated on the cycle ergometer, fitted with a facemask to measure gas exchange data (Innocor CO, Cosmed, Italia) and a heart rate monitor. The incremental cycling activity to exhaustion test started at an initial power level defined according to the participant's level (100 watts for non-cyclists and 150 watts for cyclists) and increased by 30 watts every 2 minutes until exhaustion. The end of the test was determined by volitional cessation of exercise or failure to maintain pedal cadence above 60 rpm despite strong verbal encouragement. During the first step of this maximal test, 30 trials of the RDK task were performed to set up the consistency parameter according to a staircase procedure.

Table 1. *Anthropometric and physiological characteristics of participants.*

Mean ± standard deviation	
Variables	**All**
Sample size	19
Age (years)	25±5
Height (cm)	177±7
Weight (kg)	67±9
Fat mass (%)	15±4
$\dot{V}O_2$max (ml.kg^{-1}.min^{-1})	55±8
Heart rate max (bpm)	184±9
Maximal aerobic power (W)	295±58
P_{SV1} (W)	208±55
P_{SV2} (W)	254±52
Heart rate HIE (% max)	86±6
Central temperature HIE (°C)	38,2±0,4

Note. P_{SV}: Power corresponding to the first SV1 and second SV2 ventilatory thresholds, HIE: high-intensity exercise, $\dot{V}$O2max: maximal oxygen consumption.

Before the experimental session, a familiarization session (about 1,250 trials), identical in all respects to the experimental session, was conducted to stabilize performance and control for potential learning effects, as well as to assess the physiological load of the dual task performed while cycling. The data of the familiarization session were not included in the analyses.

The experimental protocol involved high-intensity interval activity, a discontinuous mode of endurance exercise characterized by short bouts of high-intensity workloads interspersed with periods of rest. Participants completed a perceptual decision-making task at rest both before (PRE) and after (POST) eight 5-minute bouts of cycling. Each 5-minute cycling bout was followed by a 1-minute rest period, resulting in a total session duration of 47 minutes. During six of the eight cycling bouts, participants performed the perceptual decision-making task while

cycling at a workload fixed at 90% of SV1—an intensity determined during the incremental test of the preliminary session—placing them in a dual-task situation involving both cognitive and physical effort. Cardiorespiratory parameters were continuously recorded, and capillary blood samples from the fingertip were collected before and immediately after each of the 5-minute cycling bouts for the measurement of lactate and glucose levels. The skin was prepared by cleaning with alcohol, allowed to dry, and then punctured with an automated lancet. Blood samples were analyzed using a Biosen blood analyzer (EKF Diagnostics, UK).

Data Analyses

The experiment was designed to evaluate the exercise-induced effects on cognitive processes throughout high-intensity activity and immediately afterward the effortful protocol. Due to the interplay between physical demands and cognitive performance in the dual-task condition, cognitive data recorded at rest (before and after, 4916 trials) and during the dual-task condition (6 blocks while cycling, 12402 trials) were analyzed separately.

During the effortful activity, we anticipated that the impacts on decision-making processes may vary according to time spent on task. To prevent the loss of detailed aspects of how effort affects cognitive performance, we conduct analyses on three time-windows: the Beginning of the sustained physical effort spanning from 1 to 6 minutes (B1); the Middle of physical effort, covering minutes 19 to 30 (B4-B5); and the End of physical effort, encompassing minutes 37 to 48 (B7-B8). The cognitive performance recorded during the first 5-minute physical effort block (B1) was used as a baseline. This decision was made because the cognitive task is

performed in a dual-task condition (while cycling), and at that time, the physiological effect induced by exercise had not yet been fully established.

Anticipations (RTs < 200 ms; 0.13 %) were discarded from all analyses. Five subjects did not perform the perceptual task appropriately (i.e., exhibiting a percentage of accuracy below 50% or employing a stereotyped response strategy). They were excluded from the initial sample of 24 participants. We conducted a mixed-effects generalized logistic regression analysis on accuracy and performed a linear mixed-effects model analysis on correct reaction time, including 'block' as a fixed effect, with 'subject' and 'block' intercepts treated as random effects.

Regarding physiological measures, we analyzed glucose and lactate levels within linear mixed-effects models. These models included the 'sample' (PRE and B1 to B8) expressed in mmol/L as a fixed effect, with 'subject' as random effect.

The Drift Diffusion Model parameters were estimated using a hierarchical Bayesian procedure implemented with the DMC package (Heathcote et al., 2019) for the R software (R Core Team, 2016). Specifically, we considered the DDM with inter-trial variability in the drift rate (sv) and the starting point (sz), and let the drift (v), threshold (a), non-decision time (Ter) and drift rate variability vary across conditions. We used broad truncated normal distributions for the means and uniform distribution on [0,1] for the standard-deviations. In order to fit the model to the data, we used the two-steps procedure described by Heathcote et al. (2019). In a first step, we fitted each participant's data individually. The averaged resulting parameters were used in a second step as starting values for hierarchical sampling. The quality of the fit was evaluated by

visually inspecting Markov chain Monte Carlo chains, comparing predicted data according to best fitting parameters to actual data, and computing Brooks and Gelman's (1998) R statistics (see Appendix). Finally, we tested the presence of an effect of the condition on the parameter values by computing Bayesian p values (Heathcote et al., 2019).

Results

Physiological measures

The workload set for the high-intensity activity corresponded to 86% ± 7% of HRmax, ranging from 71% to 99%. Linear mixed model demonstrated a significant effect of block ($F(7, 126) = 15.114$, $p < .001$). Heart rate was lower during the first two blocks and then remained stable from the 3rd block to the end of exercise (Figure 1). Specifically, block B1 differed from the blocks B3, B4, B5, B6, B7 and B8; and the block B2 differed from the blocks B5, B6, B7 and B8.

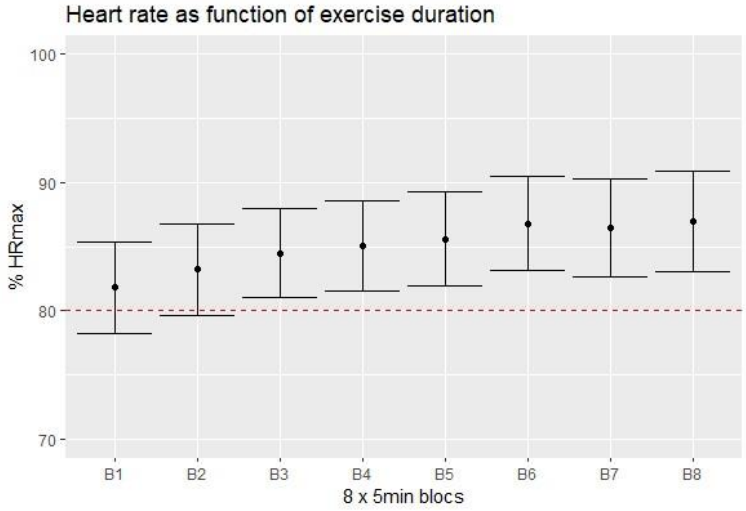

Figure 1. Heart rate as function of exercise duration (bmp/min)

The linear mixed model performed on blood sample analyses confirmed a significant impact of the effortful activity on glucose levels ($F(8, 143.03) = 6.2595$, $p < 0.001$) and on lactate levels ($F(8, 143.01) = 21.21$, $p < 0.001$) collected at the end of each 5-minute cycling bout. Post-hoc comparisons revealed lower glucose levels after each bout than before sustained physical effort (PRE = 4.70 mmol/L ± 0.76 mmol/L). No other comparisons were found to be statistically significant on glucose levels (Figure 2).

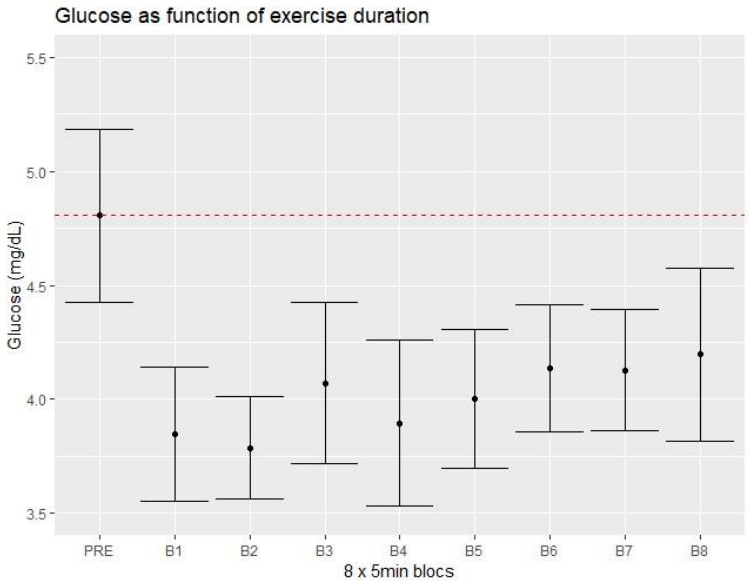

Figure 2. Glucose as function of exercise duration (mmol/L)

For the lactate concentration, higher lactate levels were observed after each 5-minute cycling bout than before physical effort (PRE = 1.66 ± 0.56 mmol/L). The lactate level after the first bout (B1 = 6.05 ± 2.22 mmol/L) was also significantly higher from those collected after B4

(4.66 ± 2.47 mmol/L), B5 (4.42 ± 2.29 mmol/L), B6 (4.49 ± 2.50 mmol/L), B7 (4.47 ± 2.66 mmol/L) and B8 (4.14 ± 2.73 mmol/L). Higher lactate level was also observed after the second bout (B2 = 5.66 ± 2.59 mmol/L) compared to B7 and B8. No other comparisons were found to be statistically significant (Figure 3).

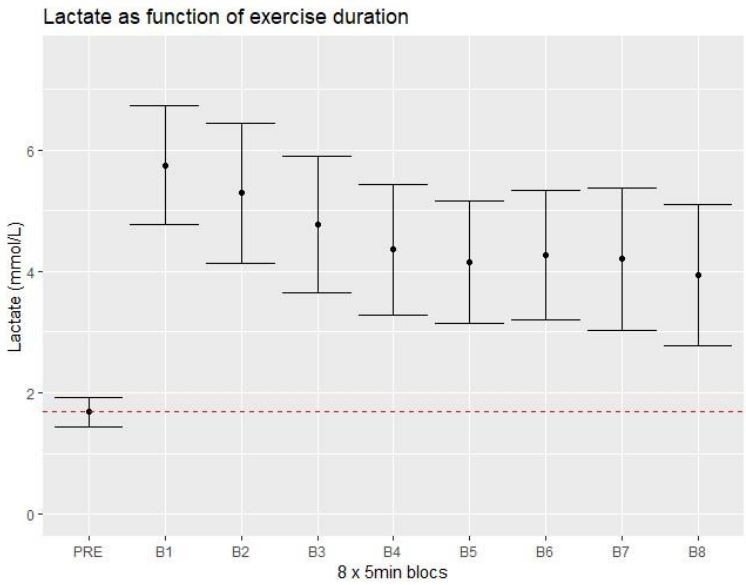

Figure 3. Lactate as function of exercise duration (mmol/L). Note: 4 mmol/L is a classical marker used to define the onset of blood lactate accumulation (OBLA), considered a valid indicator for transition from aerobic to anaerobic performance.

Behavioral data

Accuracy. The mixed-effects generalized logistic regression analysis conducted on accuracy did not reveal any significant effort-induced effects. The accuracy was not significantly different following physical effort compared to before (PRE = 87.67% vs POST = 86.64%, p =

0.891), nor during the sustained physical effort compared to the baseline (Baseline = 85.91%; Middle of physical effort = 86.28%, $p = 0.917$), nor to the End of physical effort (86.21%, $p = 0.525$).

Correct reaction time (RT). The linear mixed model conducted on correct RTs collected at rest before the effortful activity (PRE = 996 ms ± 634 ms) and after (POST = 929 ms ± 625 ms) revealed a trend toward an effect that did not reach the level of significance ($F(1, 17.316) = 3.9154$, $p = 0.064$). The linear mixed model conducted on correct RTs collected during the high-intensity activity, in the dual task situation, revealed a significant effect of block ($F(2, 16.597) = 8.0106$, $p < 0.01$). Post-hoc comparisons showed that RTs were faster at the End of effort (covering minutes 37 to 48, B7-B8: 910 ms ± 562 ms, $p < 0.001$) compared to the baseline in the dual task situation (covering minutes 1 to 6, B1: 1001 ms ± 631 ms). Reaction times in the Middle of effort (covering minutes 19 to 29, B4-B5: 942 ms ± 602 ms) were not significantly different from those in the baseline ($p = 0.269$) (Figure 4).

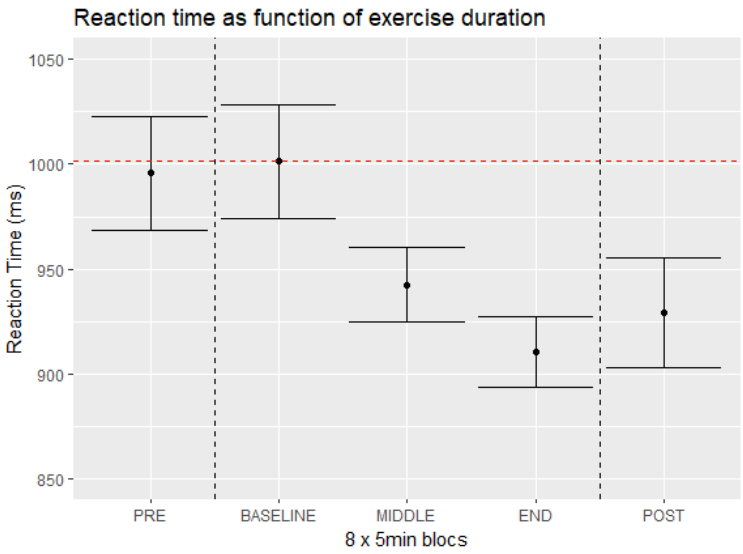

Figure 4. Reaction time (ms) as function of exercise duration Error bar represent SD.

DDM parameters. We investigated which component of the perceptual decision-making process was impact by effort by comparing the best-fitting parameters of the DDM across conditions at the group level (detailed results of the fitting procedure are available in the Supplementary Data).

Post-effort Effects. We observed significant changes in the parameters of DDM after the effortful activity compared to before. The results indicated a general improvement in cognitive processes at rest associated with perceptual decision-making. The drift rate (v) increased significantly after effort compared to before, the boundary (a) increased, and the non-decision time (Ter) decreased by approximately 64 milliseconds (Figure 5 and Table 2, for details).

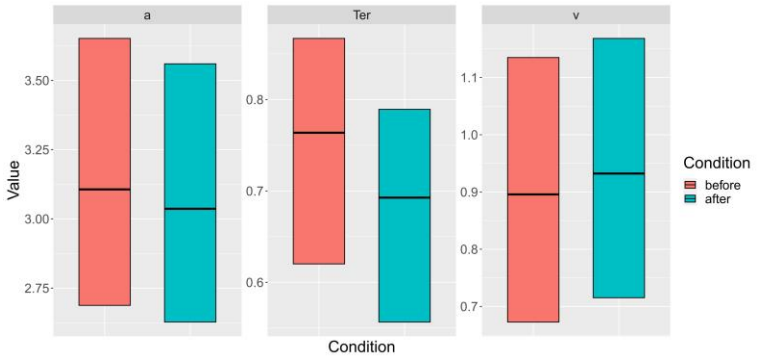

Figure 5. Diffusion model best-fitting parameters before and after high-intensity activity

Table 2. *Diffusion model best-fitting parameters before and after exercise, with 95% credible intervals and p values.*

Parameters	Before	After	Proba
v: drift rate	1.780	1.982	Delta : +0.202
	[1.695, 1.867]	[1.896, 2.068]	p<0.001
a: upper decision threshold	1.943	2.040	Delta : +0.096
	[1.880, 2.011]	[1.973, 2.111]	p < 0.05
Ter: non-decision time	0.504	0.445	Delta : -0.058
	[0.489, 0.516]	[0.431, 0.457]	p<0.001

In order to quantify the effect of the modulation of the v and a, we performed simulations, using best fitting parameters before the effortful activity (as a baseline) and varying each parameter separately to its best-fitting value after effort. According to the results of these simulations, the increase of the drift rate led to a decrease in RT by approximately 48 ms and an increase in accuracy by 1.1 percentage points. Conversely, the boundary increase resulted in an RT increase of 31 ms while improving accuracy by 0.48 percentage points.

During-effort Effects. We did not observe any modulation of the drift rate (v) in either the first or second part of the effortful activity. The boundary (a) decreased gradually as time passed, and the non-decision time (Ter) increased in the Middle of physical effort by 18 ms and decreased afterward by 14 ms (see Figure 6 and Table 3, for details).

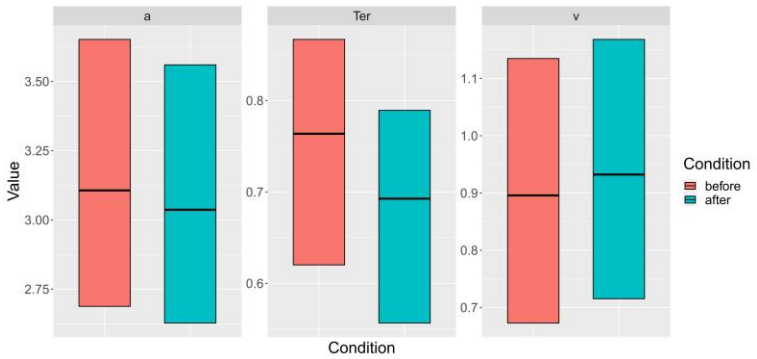

Figure 6. Diffusion model best-fitting parameters during high-intensity activity

Table 3. *Diffusion model best-fitting parameters during exercise, with 95% credible intervals and p values.*

Parameters	Baseline	Middle	End	Proba
v: drift rate	1.862 [1.758, 1.968]	1.860 [1.790, 1.934]	1.926 [1.852, 2.001]	Baseline vs End (-0.064): p=0.163 Middle vs End (-0.066): p=0.1 Baseline vs Middle (+0.002): p=0.488
a: upper decision threshold	2.158	2.027	1.959	Baseline vs End (+0.198): p<0.001

	[2.077, 2.243]	[1.973, 2.086]	[1.911, 2.011]	Middle vs End (+0.067): p=0.038 Baseline vs Middle (+0.131): p=0.005
Ter: non decision time	0.451 [0.438, 0.463]	0.469 [0.459, 0.478]	0.455 [0.447, 0.462]	Baseline vs End (-0.003): p=0.314 Middle vs End (+0.014): p=0.006 Baseline vs Middle (-0.018): p=0.008

Discussion

Summary

The present study aimed to investigate the impact of high-intensity activity on cognitive processes involved in perceptual decision-making. To achieve this, participants completed a perceptual decision task before, after, and during a dual-task condition involving both cognitive and physical effort. Cognitive processes were assessed by fitting a drift diffusion model (DDM) to behavioral data collected across these time periods.

Behavioral data indicated reduced RTs during the high-intensity activity in the dual task condition and suggested a trend toward enhanced cognitive performance at rest immediately

afterward. Moreover, the DDM provided new insights into the mechanisms underlying this enhancement by revealing changes in main diffusion model parameters (drift rate, boundary separation, and non-decision time) following effortful activity compared to before. In the dual-task condition, the impact of effortful activity on cognitive processes followed a more complex pattern, as discussed below. These findings highlight the need for further investigation to better understand the relationship between high-intensity physical effort and cognition, offering promising directions for future research.

Post-effort modulation of cognitive processes.

Reaction times recorded immediately after the effortful activity tended to be shorter (-70 ms) without a change in accuracy. This trend was further supported by computational modeling, which revealed significant post-effort changes in diffusion model parameters. Specifically, the results suggested an improvement in perceptual discrimination, more efficient non-decisional processes (perceptual encoding and motor execution), and a more cautious decision strategy.

These findings align with previous research demonstrating the impact of physiological states on cognitive processes. For instance, Ratcliff & Van Dongen (2011) showed that vigilance states induced by sleep deprivation modulate the drift rate in DDM, while Du Rietz et al. (2019) reported a positive association between high-intensity activity and changes in brain indices related to arousal and attentional allocation. In line with this, elevated neuronal activity and metabolism induced by effortful activity have been proposed to contribute to cognitive enhancement (Ide & Secher, 2000).

Beyond these neural mechanisms, systemic physiological adaptations may also play a crucial role. Cognitive improvements following high-intensity activity have been observed even after exercise cessation (Tsukamoto et al., 2016; Moreau & Chou, 2019; McMorris et al., 2016), suggesting a lasting effect of metabolic and neurochemical changes. Notably, increased blood lactate has been shown to enhance motor system reactivity and sensory perception (Coco et al., 2009, 2016), which could partially explain the observed improvements in decision-making efficiency.

One possible underlying mechanism is the increase in cerebral blood flow and oxygenation, which has been linked to cognitive benefits in response to exercise (Rooks et al., 2010). Additionally, the metabolism of catecholamines and the role of lactate—continuously produced even under fully aerobic conditions—warrant further exploration as potential contributors to these cognitive enhancements. Investigating these physiological pathways could provide deeper insight into the complex interactions between high-intensity effort and cognitive performance.

Ongoing physical effort impact on cognitive processes.

Behavioral data indicated that reaction times (RTs) were shorter at the end of the physical effort (minutes 37 to 48) compared to the first five minutes of exercise (-91 ms), with no significant modulation of accuracy. This suggests a facilitating effect of prolonged physical effort

on response speed. To better understand the cognitive mechanisms underlying this effect, we examined the parameters of the model.

First, we observed a progressive decrease in the decision threshold over the course of the physical effort, indicating that participants became less cautious as time passed. Notably, while this reduction in caution led to a substantial time gain (56 ms between the beginning and the end of physical effort), the associated decrease in accuracy remained relatively small (0.73 percentage points). This pattern suggests that physical exertion promotes a strategic shift in decision-making, where participants prioritize speed over absolute accuracy. Such an adaptation could be linked to increased arousal and enhanced neural efficiency due to heightened catecholaminergic activity (McMorris et al., 2016; Moreau & Chou, 2019) or metabolic changes such as increased cerebral lactate availability, which has been shown to influence sensorimotor processing (Coco et al., 2009; 2016). The minimal trade-off between speed and accuracy may indicate that the physiological adaptations induced by sustained effort enable participants to maintain performance efficiency while adopting a more rapid decision strategy.

Second, analysis of the non-decision time (Ter) revealed a dynamic pattern: the duration of processes unrelated to the perceptual decision increased during the middle phase of the physical effort (minutes 19 to 30) compared to the first five minutes but then diminished toward the end of the effort (minutes 37 to 48). We formulated two hypotheses. On the one hand, the initial rise of Ter may be attributed to competition for biomechanical, physiological, and/or attentional resources (e.g., McMorris, 2021; Sudo et al., 2022). On the other hand, as blood lactate

concentration appears to follow a similar pattern, the decline in lactate levels/production in the second half of the activity compared to the first half might fail to adequately support elevated brain neuronal activity and metabolism, thereby impacting cognitive performance. Indeed, the implementation of physiological adaptations, potentially coupled with improved lactate clearance and a shift in dominant energy metabolism in the later stages of physical effort, could explain the subsequent decrease in Ter (Herold et al., 2022; Hashimoto et al., 2018; Tsukamoto et al., 2016).

Finally, we found no modulation of the drift rate. This indicates that we did not observe any impact of physical effort on subjects' perceptual discrimination abilities.

At this point, it is important to acknowledge a limitation of this study: the substantial inter-individual variability in physiological responses to exercise at 90% of the first ventilatory threshold. This variability, reflected in heart rates ranging from 71% to 99% of HRmax, suggests that the relative contributions of aerobic and anaerobic metabolism differed across participants. Given that effort-induced cognitive effects may depend on metabolic demands, such heterogeneity could partly explain inconsistencies in our findings.

Post-hoc examination of individual lactate levels further confirmed this variability, as participants were roughly evenly split between those above and below the 4 mmol/L threshold, commonly associated with the onset of blood lactate accumulation (OBLA). Since OBLA marks

the transition from predominantly aerobic to anaerobic energy production, future studies should account for this factor by systematically assessing metabolic thresholds to better capture the relationship between exercise intensity, energy metabolism, and cognitive performance.

Additionally, individual differences in fitness levels may play a critical role in shaping post-exercise cognitive effects. Higher fitness levels are associated with more efficient lactate clearance, which could influence the duration and magnitude of post-exercise cognitive enhancements. Furthermore, tolerance to elevated lactate concentrations varies across individuals, potentially affecting the extent to which metabolic byproducts contribute to cognitive modulation. This underscores the need for future research to incorporate measures of aerobic capacity and lactate tolerance to refine our understanding of the interplay between physical effort, metabolic responses, and cognitive function.

By applying DDM to a perceptual decision-making task, this study provides new insights into the cognitive mechanisms underlying high-intensity exercise-induced changes. Our findings suggest that sustained physical effort facilitates a shift toward faster, albeit slightly less cautious, decision-making, potentially mediated by metabolic and neurophysiological adaptations. Furthermore, post-exercise improvements in decision efficiency highlight the complex interplay between physiological states and cognitive performance. Given the observed inter-individual variability, future research should systematically assess metabolic thresholds, aerobic fitness, and lactate clearance efficiency to refine our understanding of these effects. High-intensity exercise,

being time-efficient and ecologically valid, emerges as a promising alternative to traditional moderate-intensity protocols for cognitive enhancement, warranting further investigation.

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Declarations of interest statement

The authors declare that they have no competing interests. No funds, grants, or other support was received. The authors have no relevant financial or non-financial interests to disclose.

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