High-intensity physical activity enhances cognitive decision processes

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Abstract:

The present study aims at deciphering the effect of a high-intensity interval exercise on cognitive processes involved in perceptual decision-making through computational modelling. To that end, participants performed a perceptual decision task (RDK) before and after a high-intensity interval exercise (8 x 5min, 85 ± 8 % HRmax). Cognitive processes were measured by best-fitting parameters of a drift diffusion model (DDM) to behavioral data (accuracy and response times). Drift Diffusion modeling revealed faster non-decisional time and more efficient drift rate suggesting a better sensory encoding, a greater allocation of attentional resources and a faster processing speed following acute exercise.

Running head: Improved Decision Following Acute HIE

Key words: acute effect, exercise-cognition interaction, perceptual decision-making task, postexercise

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April 15th, 2019. Notre-Dame is burning. A fireman eventually reaches the top of the tower. He now has to decide on which side the fire should be attacked first. Will his decision be impacted by the intense physical effort he just made? And if so, which precise underlying cognitive processes are altered?

Meta-analytic studies actually suggest that acute (single) bout of physical activity enhances performances in various cognitive tasks (e.g., Psychomotor Vigilance Task, Flanker task, Critical Flicker Fusion). However, these results mainly concern moderate physical exercise intensities, which involves different cellular and molecular changes than intense physical activity such as those provided by the fireman (Herold et al., 2019), and therefore might not have the same impact on cognitive processes. Moreover, the underlying cognitive mechanisms have so far received less attention (e.g., Pontifex et al., 2019; Sudo et al., 2022).

Assessing the impact of physical exercise on cognitive processes is challenging because they are not directly observable. The cognitive computational approach provides a way to tackle this issue. It provides theoretically grounded models, whose parameters represent latent cognitive processes and can be inferred from behavioral data. Among the cognitive computational models, the Drift Diffusion Model (DDM, Ratcliff, 1978) 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), that 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 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.

In this study, we relied on the DDM to decipher the impact of high-intensity interval exercise on cognitive processes involved in a perceptual decision-making task. Specifically, we used the random dot motion task (RDK), for which the DDM has consistently provided excellent accounts of behavioral data. Behavioral data were collected before and immediately after an intense aerobic physical activity generating a stress leading to noteworthy physiological repercussions notably on heart rate, blood lactate and glycemia levels.

Method

Participants

Twenty young adults (one women; age range: 18–34; mean age: 24 years) voluntarily participated in the experiment. All participants were healthy and practiced regular physical activities (peak oxygen uptake: 55 ± 7 mL kg^{-1} min^{-1}; maximal heart rate: 185 ± 8 bpm). This sample size was determined based on prior studies reporting significant effects on cognitive performance using comparable physiological intensity (range 16 – 19 subjects; (Peirce et al., 2019)Ando et al., 2022; Ramdani et al., 2021). 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).

Apparatus

The experiment was programmed in Python, using components of the PsychoPy toolbox (Peirce et al., 2019), and was run on a PC computer natively running Windows 10. Responses were communicated to the computer by means of two buttons (one for each hand).

Random dot motion task (RDK)

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 visited the laboratory on three occasions (a preliminary session, a familiarization session, and an experimental session) at least 48h apart. Participants were

seated on an upright cycle ergometer (Lode, Excalibur, Netherland), which included two thumb response buttons on the right and left handle grips. A screen computer was placed at eye level in front of the participant at 1m.

The preliminary session was carried out to individually adjust the difficulty of the cognitive task, determine the $\dot{V}O_2max$ and estimate the power associated to the ventilatory thresholds (Wasserman, 2012) (see Table 1 for details). Participants were seated on the cycle ergometer (Lode Excalibur Sport, Groningen, The Netherlands), fitted with a facemask to measure gas exchange data (Innocor CO, Cosmed, Italia) and a heart rate monitor. The incremental cycling exercise 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 was performed to set up the consistency parameter according to a staircase procedure.

	Mean ± standard deviation		
Variables	**All**	Male	Female
Sample size	20	19	1
Age (years)	24±5	24±5	32
Height (cm)	177±7	178±6	161
Weight (kg)	67±9	68±9	51
Fat mass (%)	15±4	14±3	27,9
$\dot{V}O_2max$ ($ml.kg^{-1}.min^{-1}$)	55±7	56±6	35,7
Heart rate max (bpm)	185±8	185±8	185
Maximal aerobic power (W)	295±57	300±53	190
P_{SV1} (W)	204±56	208±55	130
P_{SV2} (W)	253±51	258±47	160
Heart rate HIE (bpm)	157±16	157±16	158
Heart rate HIE (% max)	85±8	85±9	86
Central temperature HIE (°C)	38,2±0,4	38,2±0,4	37,8

Table 1. Anthropometric and physiological characteristics of participants. P_{SV}: Power corresponding to the ventilatory threshold, HIE: high-intensity exercise, $\dot{V}O_2max$: maximal oxygen consumption.

A familiarization session (about 1 250 trials), identical in all respects to the following experimental cognitive session, was carried out in order seemed to minimizing potential of learning or practicing effects, avoiding individual differences inherent to a design protocol, and excluding day-to-day variations of performance. During this session, participants

completed the cognitive task at rest before and after the completion of the high-intensity interval exercise (lasting about 48 min), then the exercise started with 30s step performed at 75 Watts, and the intensity gradually increases in power up to 90% of the first ventilatory thresholds (SV1). This fairly low intensity was deliberately chosen in order to consider the additional physiological cost induced by the cognitive task. At this intensity, corresponding to an individual heart rate range between 62-97% HRmax, participants carry out 5 min cycling interspersed with 1 min active recovery. The RDK task was performed continuously while cycling (average 130 trials, ranged from 68 to 176 trials). Participants had to identify the motion direction (leftward vs. rightward) by pressing the corresponding button with their left or right thumb. They were instructed to respond as quickly and accurately as possible. Capillary blood samples from the fingertip were taken just before and after exercise to measure lactate and glucose. The skin was cleaned with alcohol, allowed to dry and then punctured with an automated lancet. Blood sample was analyzed using Biosen blood analyzer (EKF diagnostics, UK). During the experimental session, participants completed the exact same protocol.

Data Analyses

The analyses presented here focus exclusively on pre- and post-exercise data collected at rest. The data recorded during high-intensity exercise, compared to after exercise, induces very different physiological responses which implied other cognitive processes. They will thus be the object of another study. Anticipations (RTs < 150 ms; 0.11 %) were discarded from all analyses. Two subjects did not perform the perceptual task appropriately (i.e., percentage of accuracy under 50%) and were excluded from the initial sample of 22 participants.

The Drift Diffusion Model (DDM) 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) and nondecision time (Ter) vary across conditions. We used truncated normal priors at the individual level (bounds: [0,5] for a, [-5,5] for v, and [0,1] for all other parameters). At the group level, we assumed 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 Supplemental Data). Finally, we tested the presence of an effect of the condition (before vs. after exercise) on the parameter values by computing Bayesian *p* values (Heathcote et al., 2019).

Results

Physiological measures

The intensity set up during the high-intensity interval exercise corresponds to 85 ± 8 % of the maximal hearth rate (HRmax) (range from 62 to 97 % of HRmax). Paired t-test showed higher heart rate at the end of the 8th block (159 ± 16 bpm) compared to the 1st block (151 ± 16 bpm, t = -4.71, p < .001, d = 19, CI [-11.97, -4.60]) showing a classical derive of heart rate through the high-intensity interval exercise (Figure 1). Blood sample analyses confirmed the physiological repercussions of the protocol on lactate and glucose levels. Following exercise lactate concentration was higher (+2.2 ± 0.7 mml^{-1}, t = -4.77, p = 2.54e-05, df = 39, CI [-2.28, -0.92]) and glucose was lower (-0.6 ± -1 x 10^{-3} mml^{-1}, t = 3.85, p < .01, df = 39, CI [0.28, 0.92]) than before exercise.

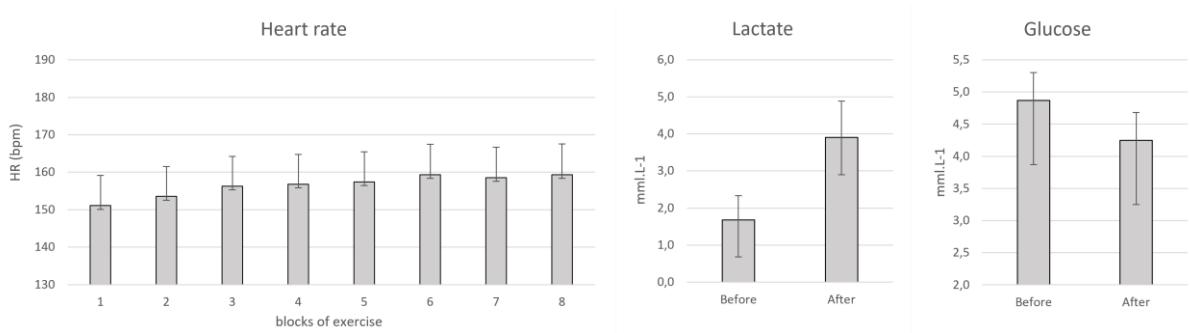

Figure 1. Heart rate (bpm) evolution during the high-intensity interval exercise, lactate and glucose levels (mml.L^{-1}) before and after exercise. Error bar represent ½ SD.

Behavioral data

Accuracy (%) by condition (before vs. after exercise) and RT (s) by accuracy and condition are presented in the Table 2.

		Before	After
Percentage of correct response		87% (34)	87% (34)
Mean RT	RT correct	0.99 (0.63)	0.92 (0.63)
	RT error	1.4 (0.79)	1.3 (0.79)

Table 2. Response times in second and percentage of accuracy averaged across subjects before and after high-intensity intermittent exercise. Standard deviation are in parentheses.

DDM parameters

Visual inspection of Markov chain Monte Carlo chains (Supplemental Data, graph 1), comparison between predicted and actual data (Supplemental Data, graph 2), and Brooks and Gelman's (1998) R statistics (Supplemental Data, table 4) show that the estimation procedure was satisfactory.

We investigated which component of the perceptual decision-making process was impact by exercise 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). Table 3 shows the parameter estimates before and after exercise and the probability value associated: the drift *v* rate increases significantly following exercise compared to before, the non-decision time *Ter* decreases by about 70 ms, and the boundary *a* increases. Additional simulations allow to quantify the impact of the variation of the drift and the threshold. The increase in the drift and the threshold (drift rate: +0.010, threshold: + 0.0044) have opposite effects of similar size on RT (about 30 ms), and very small effects on accuracy.

	Before	After	Proba (after>before)
v = drift rate	1.7 [1.1,2.4]	1.8 [1.2,2.6]	0.023
a = upper decision threshold	2.0 [1.7, 2.3]	2.1 [1.8,2.4]	0.045
Ter = non decision time	0.49 [0.36,0.59]	0.40 [0.05,0.74]	<0.01

Table 3. Diffusion model best-fitting parameters before and after intense exercise, with 95% credible intervals.

Discussion

The present study aimed at deciphering the subsequent effect of a high-intensity interval exercise on cognitive processes involved in perceptual decision-making. To that end, participants performed a perceptual decision task (RDK) before and after a high-intensity interval exercise (i.e., 8 x 5min, 85 ± 8 % HRmax). Cognitive processes were measured by best-fitting parameters of a drift diffusion model (DDM) to behavioral data (accuracy and

response times). We found that high-intensity interval exercise notably modulates non-decisional and decisional processes immediately following physical activity.

Specifically, we observed a diminution of non-decision time (*Ter*), which measures the mean duration time required for processes unrelated to the decision process in perceptual decision-making task. This observation is consistent and comparable with the results reported by Davranche et al. (2005, 2006) showing a facilitation of non-decisional processes during a single bout of moderate physical activity. Using the decomposition of reaction time, with respect to the electromyographic activity of response agonists (a chronometric and electromyographic study), these studies actually showed that exercise enhances motor processes involved in response execution as well as peripheral sensory processes involved in early sensory operations. Additionally, we observed an increase of the drift rate (v) after completion of high-intensity interval exercise. This finding is in line with the fact that (i) high-intensity physical activity is positively associated with changes in brain-indices associated with arousal levels and attention allocated to the task (Du Rietz et al., 2019) and (ii) vigilance state induced by sleep-deprivation modulates the drift rate in DDM (Ratcliff & Van Dongen, 2011).

These results are fully consistent with the increase in central nervous system excitability associated with the release of central catecholamines during exercise and more particularly during such high-intensity exercise. The massive release in catecholamines renders the organism more receptive to sensory information (Moxon et al., 2007) and more prone to react (Davranche et al., 2015). Moreover, other peripheral biomarkers specific to high-intensity exercise such as circulating lactate (Hashimoto et al., 2021), blood glucose, circulating cortisol level or neurotrophic factors could also contribute to cognitive changes in a synergistic way. All these adaptive modulations (for a review see, Singh & Staines, 2015) most likely participate to enhance motor cortex sensitiveness to upstream influences, thereby increasing sensory sensitivity (promoting stimulus encoding), raising arousal level (accelerating processing speed) and modulating corticospinal excitability (promoting the execution of the response).

We also observe a modulation of the decision threshold (a), with more cautious decisions after exercise. This effect is, however, statistically more fragile. To the best of our knowledge, there is little reason to expect that physical exercise should modulate speed-accuracy trade-off. For instance, neither the bromocriptine (a dopamine receptor agonist, Winkel et al., 2012), nor sleep deprivation (Ratcliff & Van Dongen, 2011) were found to modulate decision threshold. Therefore, the robustness of the observed modulation of decision

threshold after high intensity exercise, as well as the potential underlying physiological mechanisms remain open to further investigations.

Most studies aiming at better understanding the acute effects of physical activity on cognitive processes, have focused on moderate-intensity continuous exercise. It is only very recently that there has been a growing interest in high-intensity exercise. By applying DDM model on a perceptual decision-making task, the present results provide a new insight into cognitive mechanisms underlying high-intensity exercise-induced changes. Faster non-decisional time and more efficient drift rate suggest a better sensory encoding, a greater allocation of attentional resources and a faster processing speed following exercise. Less time-consuming, more ecological and particularly efficient, high-intensity exercises appear a very promising alternative to traditional light- to moderate- exercises.

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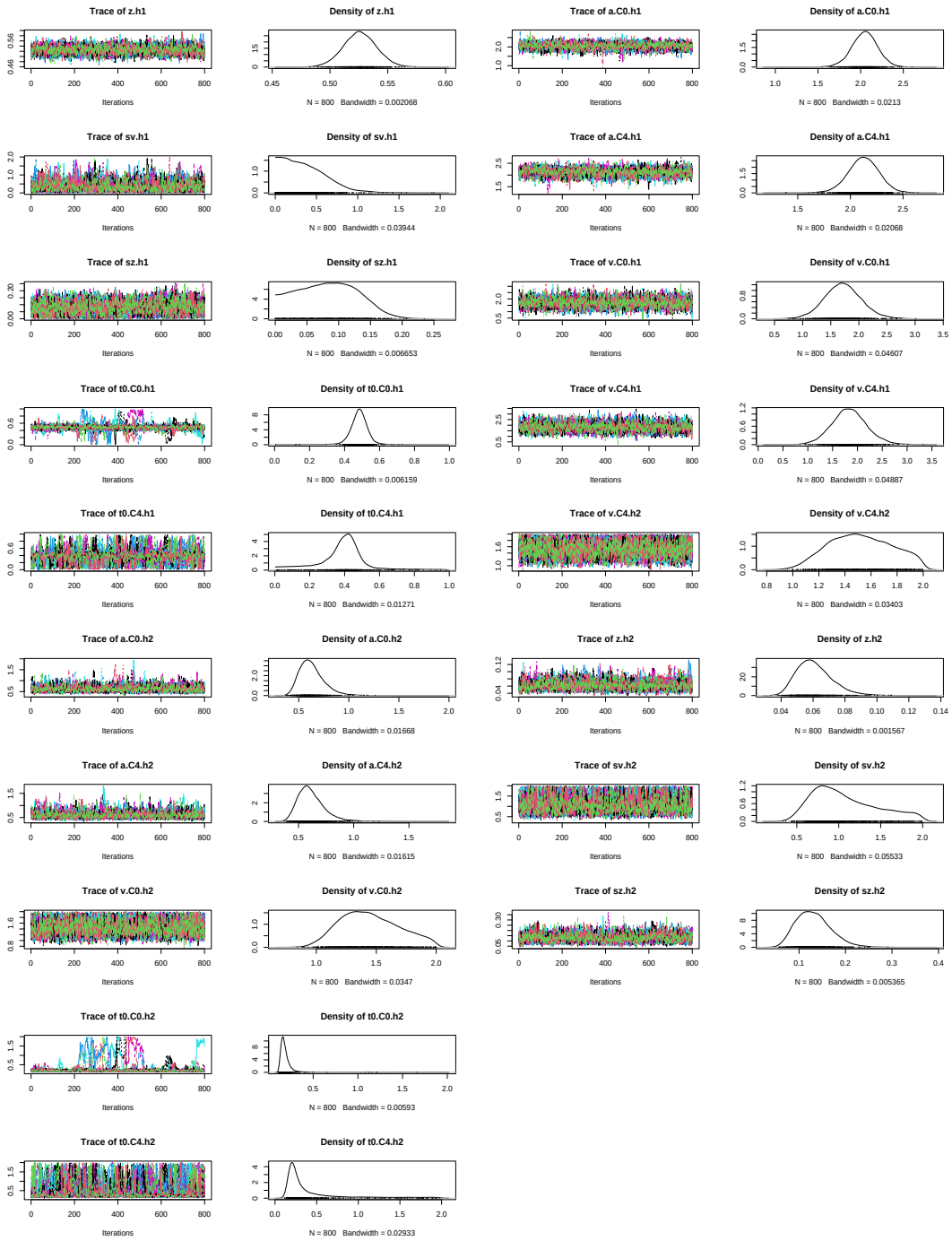
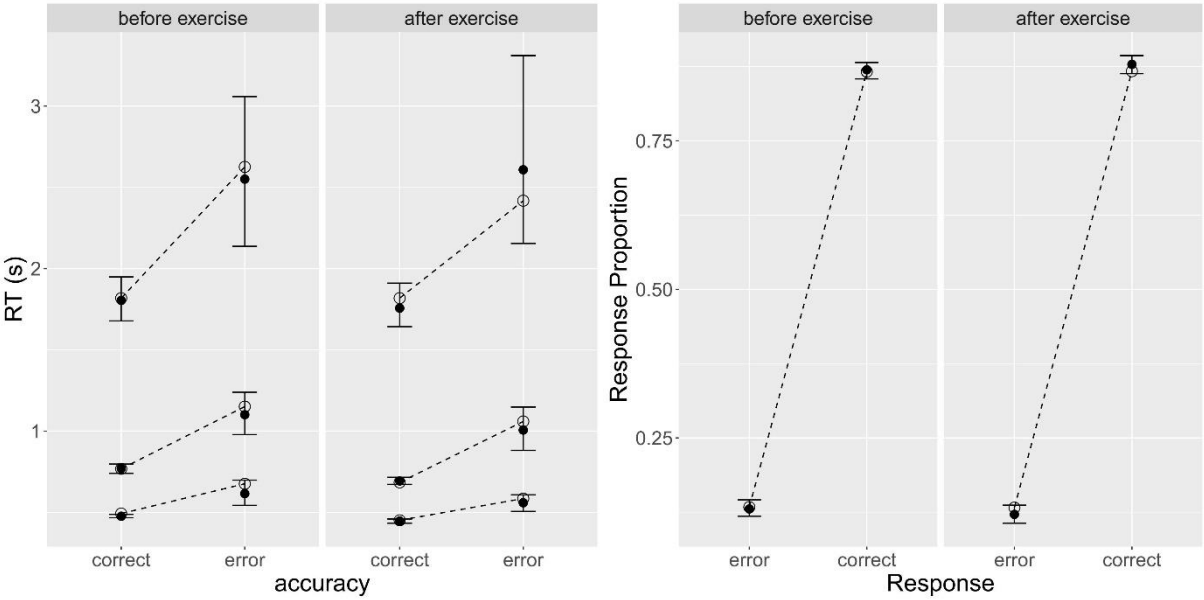
Supplementary data

Graph 1: Markov chain Monte Carlo trace and density of DDM parameters (z: starting point, sv: drift variability, sz: starting point variability, t0: non-decisional time (Ter), a: decision thresholds, v: drift) before (C0) and after (C4) high-intensity interval exercise.



Graph 2: Fit quality for Accuracy rate (left) and Responses time (right) before and after high-intensity interval exercise.



Note. Open points: data; solid points: model prediction; error bars show the corresponding 95% credible intervals.

Table 4: Group parameters estimates

		2.5%	50%	97.5%	Rhat
Hyper location					
	z	0.50	0.53	0.55	1.0
	sv	0.02	0.33	1.02	1.0
	sz	0.01	0.08	0.17	1.0
			Before		
	a	1.74	2.05	2.34	1.0
	v	1.07	1.71	2.40	1.0
	Ter	0.36	0.48	0.59	1.0
			After		
	a	1.82	2.13	2.41	1.0
	v	1.16	1.83	2.56	1.0
	Ter	0.05	0.40	0.74	1.0
Hyper scale	z	0.04	0.06	0.09	1.0
	sv	0.51	1.00	1.91	1.0
	sz	0.07	0.13	0.21	1.0
			Before		
	a	0.44	0.61	0.94	1.0
	v	1.03	1.43	1.93	1.0
	Ter	0.12	0.17	0.84	1.1
			After		
	a	0.43	0.60	0.92	1.0
	v	1.09	1.51	1.96	1.0
	Ter	0.15	0.26	1.76	1.0

Note. Ter: non-decisional time, a: decision thresholds, v: drift, Rhat: Brooks and Gelman's (1998) R statistics

Table 5. Individual parameters median before and after high-intensity interval exercise

				Before			After		
Subject	z	sz	sv	a	v	Ter	a	v	Ter
1	0.47	0.14	1.11	1.72	2.83	0.45	1.75	3.25	0.37
2	0.51	0.14	0.14	3.08	0.87	0.75	3.04	0.94	0.69
3	0.56	0.14	0.40	2.47	0.27	0.47	2.51	0.49	0.58
4	0.57	0.14	0.37	1.96	1.55	0.56	1.83	1.35	0.36
6	0.42	0.12	0.80	1.64	0.71	0.33	1.58	1.19	0.26
7	0.47	0.12	0.83	1.17	0.76	0.63	1.29	0.46	0.46
8	0.54	0.23	1.62	1.62	2.34	0.35	1.92	2.85	0.28
9	0.60	0.12	1.42	1.59	4.79	0.36	1.77	4.59	0.28
10	0.56	0.16	0.56	1.92	3.14	0.34	2.07	3.70	0.33
12	0.49	0.13	0.27	2.97	0.23	0.68	2.80	0.11	0.84
14	0.63	0.12	0.34	1.98	0.42	0.46	2.24	0.30	0.47
17	0.52	0.12	0.32	2.55	0.78	0.70	2.76	1.40	0.56
18	0.56	0.13	0.68	1.42	3.23	0.36	2.05	3.18	0.32
19	0.58	0.13	0.87	1.48	3.45	0.35	2.40	4.17	0.26
20	0.56	0.13	0.35	2.30	0.31	0.63	2.75	0.44	0.10
22	0.50	0.15	0.32	1.99	1.42	0.38	1.33	2.08	0.43
23	0.54	0.12	0.24	2.83	1.24	0.46	2.88	0.89	0.66
24	0.45	0.12	1.37	2.72	3.03	0.32	2.14	2.41	0.33
25	0.49	0.13	1.02	1.59	1.28	0.77	1.36	1.26	0.55
26	0.49	0.14	0.82	2.08	1.94	0.35	2.21	1.99	0.34
Mean	0.53	0.14	0.69	2.05	1.73	0.49	2.13	1.85	0.42

Note. Z: starting point, sv: drift rate variability, sz: starting point variability, Ter: non-decisional time, a: decision thresholds, v: drift rate.