Exploring Decision-making Processes: The Impact of Acute High-Intensity Aerobic Exercise

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Abstract:

The present study aims to investigate the impact of acute high-intensity aerobic exercise on cognitive processes related to perceptual decision-making through computational modelling. Participants completed a perceptual decision task before, after, and while exercising at high-intensity aerobic intensity (eight 5-minutes blocks at 90% of the first ventilatory threshold SV1; 86 ± 7% HRmax). Cognitive processes were assessed by determining the best-fitting parameters of a drift diffusion model (DDM) based on behavioral data (accuracy and reaction times). The results showed decreased reaction times while exercising and suggested a trend toward enhanced cognitive performance immediately following exercise. Significant changes in the main parameters of the drift-diffusion model were observed immediately post-exercise compared to pre-exercise, indicating an improvement in perceptual discrimination and more efficient non-decisional processes (perceptual encoding and motor execution), associated with a more cautious decision strategy. The impact of exercise on cognitive processes during exercise presented a different picture. The decision threshold decreased over the course of the exercise, indicating that participants became less cautious as time passed. Additionally, the time required for processes unrelated to the perceptual decision increased in the first part of exercise and diminished afterward, suggesting a nuanced and dynamic evolution of decision-making over the course of the exercise.

Running head: Decision Model Analysis of Physical Exercise Effects

Key words:

Computational Modelling, Acute exercise, Exercise-cognition interaction, Perceptual decision-making, Exercise-induced effect, Drift Diffusion Model

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Introduction

April 15, 2019. Notre-Dame is ablaze. After a strenuous climb, a firefighter finally reaches the top of the tower. Now, she must decide which side of the raging fire to attack first. Is her decision affected by the exercise-induced effect? And if so, which specific underlying cognitive processes are altered during and after this intense physical demand?

It is well established that acute moderate-intensity exercise 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 exercise on cognitive performance, contrasting with the less clarified impacts of high-intensity aerobic exercise (Sudo, Costello, McMorris & Ando, 2022; Zheng et al., 2021; Pontifex et al., 2019). Despite theoretical expectations, the literature regarding the effects of high-intensity exercise on cognitive performance is inconclusive and contradictory (e.g., McMorris, 2021; Moreau and Chou, 2019). While some studies support the notion of impaired cognitive performance following high-intensity exercise, others suggest no significant effects or even improvements. This ambiguity highlights the complexity of the relationship between high-intensity exercise and cognitive function, indicating that further research is needed to fully understand these effects. The emphasis on moderate-intensity exercise, primarily driven by methodological considerations, has left a gap in our comprehension of the interaction between physical exercise and cognitive performance, especially when physiological demands are substantial.

The impact of high-intensity exercise, defined as physiologic demand exceeding 80% maximal oxygen uptake (McMorris et al., 2016), or equivalent [e.g., exceeding 80% maximal heart rate (HR)], warrants deeper investigation. This is particularly crucial because it is associated with more pronounced cellular and molecular changes than conventional exercises (Herold et al., 2019). Consequently, its influence on cognitive processes, likely mediated by specific peripheral biomarkers associated with high-intensity exercise, 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 the existing literature. These induced systemic physiological adaptations could have implications for the entire organism, potentially altering cognitive functioning. For example, they may enhance motor cortex sensitivity to upstream influences, increase sensory sensitivity (promoting stimulus encoding), raise arousal levels (accelerating processing speed), or modulate corticospinal excitability (promoting the execution of the response).

Quantifying the influence of physical exercise 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 interval 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),

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 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 high-intensity aerobic exercise sessions (eight 5-minutes blocks, at 90% of the first ventilatory threshold SV1). Cognitive processes were assessed by determining the best-fitting parameters of a model based on behavioral data (accuracy and reaction times).

Method

Participants.

Nineteen young adults (one woman, age range: 18–34; mean age: 25 years) voluntarily participated in the experiment. All participants were healthy and practised regular physical activities (peak oxygen uptake: 55 ± 8 mL kg−1 min−1; maximal heart rate: 184 ± 9 bpm). This sample size was determined based on prior studies reporting significant effects on cognitive performance using comparable physiological intensity (range 16 – 19 subjects; (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.

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).

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 centred 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 the 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 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**
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

Table 1. Anthropometric and physiological characteristics of participants. PSV: Power corresponding to the ventilatory threshold, HIE: high-intensity exercise, V̇O2max: maximal oxygen consumption.

A familiarization session (about 1,250 trials), identical in all respects to the experimental session, was conducted to ensure performance stability and eliminate any potential practice-related effects before the experimental session. The data of the familiarization session were not included in the analyses. The experimental protocol involved a high-intensity intermittent aerobic exercise, corresponding to corresponding to an intensity fixed at 90% of SV1, and lasting 48 minutes. Participants completed the cognitive task before exercise (PRE), during six of the eight 5-minutes exercise sequences, and after

exercise (POST). Participants gradually increased their pedaling intensity to reach the predetermined power corresponding to 90% of SV1. At this intensity level, participants engaged in 8 sets of 5-minute cycling bouts interspersed with 1 minute of recovery. Cardiorespiratory parameters were continuously recorded during the exercise, and capillary blood samples from the fingertip were collected before and immediately after each of the eight blocks 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 experimental protocol was designed to evaluate the exercise-induced effects on cognitive processes throughout the exercise duration and immediately following the exercise. Due to the substantial increase in cognitive load induced by the dual-task condition, cognitive data recording at rest (before and after, 4916 trials), and in a dual-task condition (6 blocks while cycling, 12402 trials) were analyzed separately.

During exercise, we anticipated that the effects on decision-making processes may vary according to exercise duration. To prevent the loss of detailed aspects of how exercise affects cognitive performance, we conduct analyses on three time windows: the Beginning of the exercise spanning from 1 to 6 minutes (B1); the Middle of the exercise, covering minutes 19 to 30 (B4-B5); and the End of the exercise, encompassing minutes 37 to 48 (B7-B8). The cognitive performance recorded during the first 5-minute exercise 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 exercise-induced effect 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., percentage of accuracy under 50% or undesirable 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 intensity level set during the high-intensity interval exercise corresponds to 86% ± 7% of HRmax (ranging from 71% to 99% of HRmax). Linear mixed model demonstrated a significant effect of block ($F(7, 126) = 15.114$, $p < .001$). Heart rate was lower during the blocks B1 and B2 and then remained stable from the 3th 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.

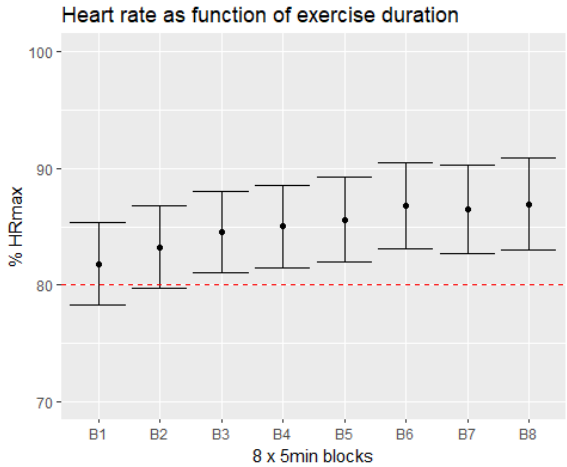

Figure 1. Heart rate as function of exercise duration (bmp/min)

The linear mixed model performed on blood sample analyses confirmed a significant impact of high-intensity interval exercise 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 block of exercise. Bonferroni comparisons revealed lower glucose levels after each of the eight blocks than before exercising (PRE = 4.70 mmol/L ± 0.76 mmol/L). No other comparisons were found to be statistically significant on glucose levels (Figure 2).

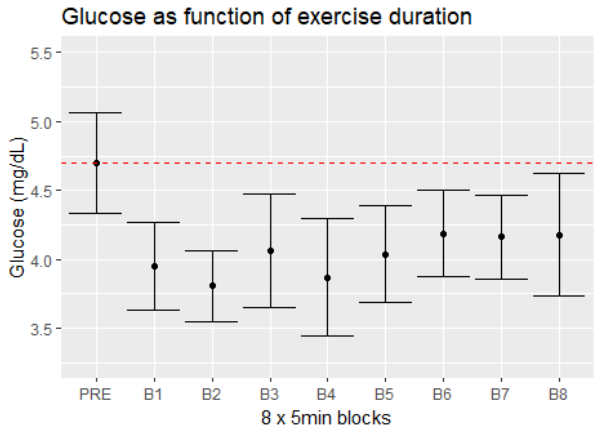

Figure 2. Glucose as function of exercise duration (mmol/L)

For the lactate concentration, higher lactate levels were observed after each of the eight blocks than before exercising (PRE = 1.66 ± 0.56 mmol/L). The lactate level after the first block (B1 = 6.05 ± 2.22 mmol/L) was also significantly higher from those collected after the blocks 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 block (B2 = 5.66 ± 2.59 mmol/L) compared to the block B7 and B8. No other comparisons were found to be statistically significant (Figure 3).

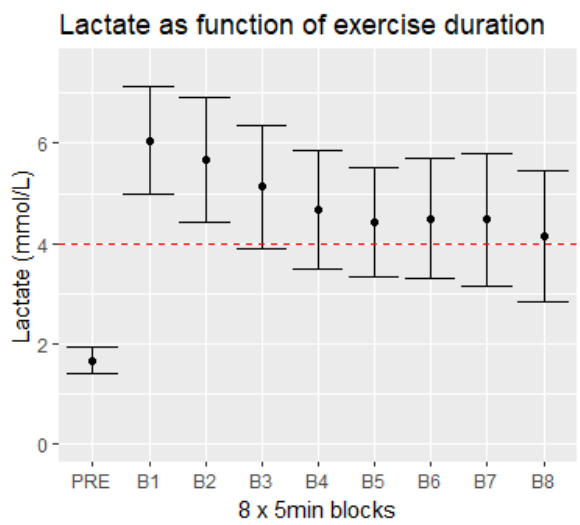

Figure 3. Lactate as function of exercise duration (mmol/L). Note: 4 mmol/L is a classical marker used to define the onset of blood lactate accumulation (OBLA), considered a valid indicator for transition from aerobic to anaerobic performance.

Behavioral data

Accuracy.

The mixed-effects generalized logistic regression analysis conducted on accuracy did not reveal any significant exercise-induced effects. The accuracy was not significantly different following exercise compared to before (PRE = 87.67% vs POST = 86.64%, p = 0.891), nor

during exercise compared to the baseline (Baseline = 85.91%; Middle of exercise = 86.28%, p = 0.917), nor to the End of exercise (86.21%, p = 0.525).

Correct reaction time (RT).

The linear mixed model conducted on correct RTs collected before exercise (PRE = 996 ms ± 634 ms) and after exercise (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 exercise 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 the exercise (covering minutes 37 to 48, B7-B8: 910 ms ± 562 ms, $p < 0.001$) compared to the baseline (covering minutes 1 to 6, B1: 1001 ms ± 631 ms). Reaction times in the Middle of the exercise (covering minutes 19 to 29, B4-B5: 942 ms ± 602 ms) were not significantly different from those in the first exercise block ($p = 0.269$).

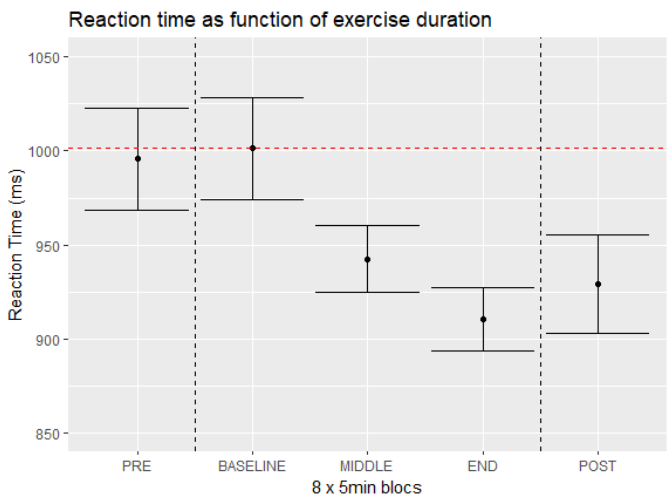

Figure 4. Reaction time (ms) as function of exercise duration Error bar represent SD.

DDM parameters.

We investigated which component of the perceptual decision-making process was impact by 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).

Post-Exercise Effects.

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

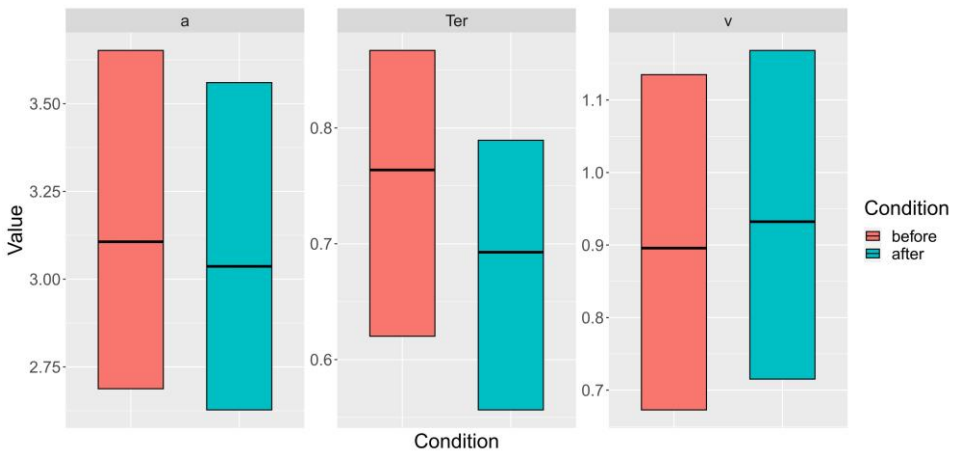

Figure 5. Diffusion model best-fitting parameters before and after intense exercise

In order to quantify the effect of the modulation of the v and a, we performed simulations, using best fitting parameters before exercise as a baseline, and varying each parameter separately to its best-fitting value after exercise. 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.

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

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

During-Exercise Effects.

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

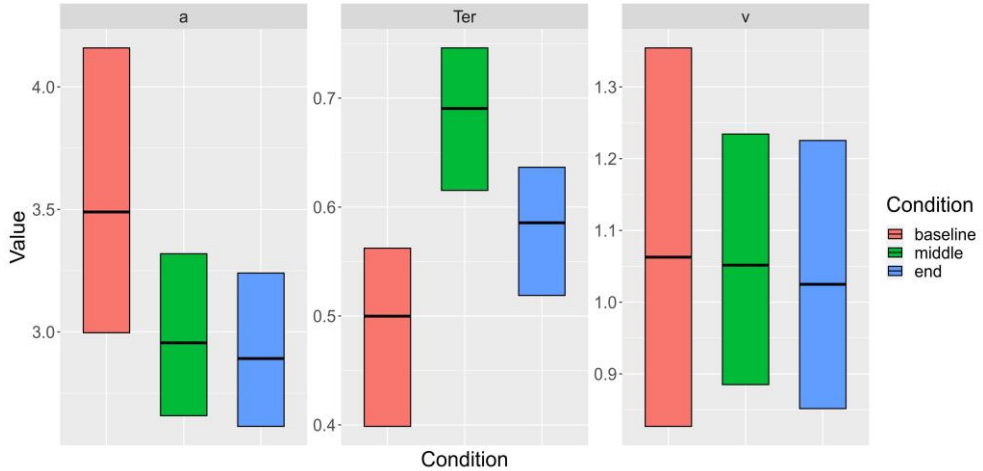

Figure 6. Diffusion model best-fitting parameters during exercise

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 [2.077, 2.243]	2.027 [1.973, 2.086]	1.959 [1.911, 2.011]	Baseline vs End (+0.198): p<0.001 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

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

Simulations show that the decrease of the boundary between the baseline block and the Middle of exercise resulted in a reduction of RT of 37 ms and a decrease of accuracy by 0.49 percentage points. The decrease of the boundary between the Middle of exercise and the End of exercise induced a further reduction of RT of 19 ms and an additional decrease of accuracy by 0.24 percentage points.

Discussion

Summary.

The present study aimed to investigate the impact of high-intensity interval exercise on cognitive processes related to perceptual decision-making. To achieve this, participants completed a perceptual decision task before, after, and while exercising at high-intensity.

Cognitive processes were assessed by determining the best-fitting parameters of a drift diffusion model (DDM) based on behavioral data collected during these time periods.

Behavioral data indicated decreased RTs while exercising and suggested a trend toward enhanced cognitive performance immediately following exercise. Moreover, the DDM model provided new insights into the underlying processes of this enhancement by revealing that the main parameters of the diffusion model were impacted immediately post-exercise compared to pre-exercise. The exercise-induced impacts on cognitive processes during exercise revealed a more complex pattern, as discussed further below. These findings emphasize the importance of additional exploration and clarification to deepen our understanding of the relationship between high-intensity exercise and cognitive processes, offering promising avenues for future research.

Ongoing exercise impact on cognitive processes.

Behavioral data results indicated faster RTs at the End of the exercise (covering minutes 37 to 48) compared to the first 5 min-exercise block (-91 ms), with no modulation of accuracy, suggesting a facilitating effect of intense exercise. Inspection of DDM parameters allows for a more specific identification of the underlying cognitive process at play.
Firstly, we observed a decrease in the decision threshold over the course of the exercise, indicating that participants became less cautious as time passed. It is noteworthy that while the time gain induced by this change is substantial (56 ms between the Beginning and the End of the exercise), the associated decrease in accuracy is relatively small (0.73 percentage points).
Secondly, the evolution of the non-decision time (Ter) showed that the mean duration time required for processes unrelated to the perceptual decision increased in the Middle of exercise (covering minutes 19 to 30) compared to the first 5 min-exercise block, and diminished afterward until the End of the exercise (covering minutes 37 to 48). We hypothesize that the initial rise of Ter could be attributed to competition for biomechanical, physiological, and/or attentional resources (e.g., McMorris, 2021; Sudo et al., 2022). Subsequently, the implementation of adaptations, potentially coupled with improved lactate clearance and a shift in the dominance of energy metabolism in the second part of the exercise, could explain the subsequent decrease in Ter (Herold et al., 2022; Hashimoto et al., 2018). Finally, we found no modulation of the drift rate. This indicates that we did not observe any impact of exercise on subjects' perceptual discrimination abilities.

Our results contrast with recent reviews showing that cognitive performance is more likely to be impaired during and after high-intensity exercise (Sudo et al., 2022; Zheng et al., 2021). This suggests that the impact of intense exercise on cognitive processes is highly dependent on the specificity of the experimental protocol. It therefore requires cautious interpretation and calls for standardisation and replication of experimental studies (Pontifex et al., 2019).

Post-exercise modulation of cognitive processes.

Reaction time recorded after exercise completion tended to be faster (-70 ms), without change in accuracy. This trend was confirmed by the computational modelling approach, which revealed that the main parameters of the diffusion model were impacted

immediately post-exercise compared to pre-exercise, suggesting an improvement of perceptual discrimination, more efficient non-decisional processes (perceptual encoding and motor execution), associated with a more cautious decision strategy. These findings are in line with the fact that (i) high-intensity physical exercise 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).

Despite numerous studies investigating the effects of exercise on cognition, the impact of high-intensity exercise on subsequent cognitive performance is not yet fully understood (Browne et al., 2017; McMorris, 2016; Moreau & Chou, 2019). One reason for this lack of clarity is that neurochemical explanations, while providing insights into the impact of exercise on cognitive function during physical exercise, may not completely elucidate the effects that occur after exercise. Notably, because the pronounced cellular and molecular changes induced by intense stress are temporary, and the rapid return to baseline after exercise cessation cannot solely account for the subsequent effects observed following exercise. Further research is thus necessary to determine the extent to which pronounced cellular and molecular changes induced by intense exercise may underlie the differences in decision-making cognitive processes observed after completion.

Among the hypotheses currently under investigation, the increase in cerebral blood flow is an adaptive mechanism induced by intense exercise that could potentially play a role in the observed cognitive improvement after intense exercise. Indeed, in contrast to light to moderate physical exercise, higher levels of cerebral blood flow and oxygenation have been reported during high-intensity exercises (Rooks, Thom, McCully, & Dishman, 2010). Another hypothesis currently under investigation involves the metabolism of catecholamines. Specifically, the changes induced by increased demand during intense exercise could persist for a certain period after exercise cessation, potentially explaining an enhancement in certain cognitive processes (Moreau & Chou, 2019, McMorris et al., 2016).

Limitations.

The first limitation in this study is the variability across subjects in physiological responses induced by exercising at 90% of the first ventilatory threshold (ranging from 71% to 99% of HRmax). This variability might contribute to discrepancies in results, as the exercise-induced effects on cognition may depend on the degree to which aerobic relative to anaerobic energetic metabolism is required. After completing the study, we examined individual lactate levels to determine how many subjects were above and below 4 mmol/L, commonly known as the onset of blood lactate accumulation (OBLA). OBLA is a valid indicator for the transition from predominantly aerobic to anaerobic energy production. Participants exhibited different levels, with half the subjects above and the others below the threshold level of 4mmol/L of blood lactate concentration. Future experiments should be upgraded to avoid such discrepancies in physiological responses across subjects. Improving the understanding of individual responses, such as examining lactate levels, could contribute to a better understanding of the biochemical factors influencing cognitive changes during and following exercise.

Finally, it should be stressed that we compared cognitive performance during specific time windows using cognitive data recorded during the first 5-minute exercise block as a baseline. However, according to Moreau and Chou's meta-analysis (2019), high-intensity exercise more often leads to cognitive enhancement (at least after the bout) when performance is compared with rest rather than when it is compared with lower-intensity exercise. As a result, our chosen baseline, corresponding to cognitive performance recorded while cycling at a time when exercise-induced effects were not yet fully established, could potentially introduce Type I errors. Therefore, in future experiments, we will benefit from designing protocols to perform comparisons with resting conditions and conducting cognitive tasks during the recovery phase of intermittent exercise, immediately following the completion of each block.

Conclusion.

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. 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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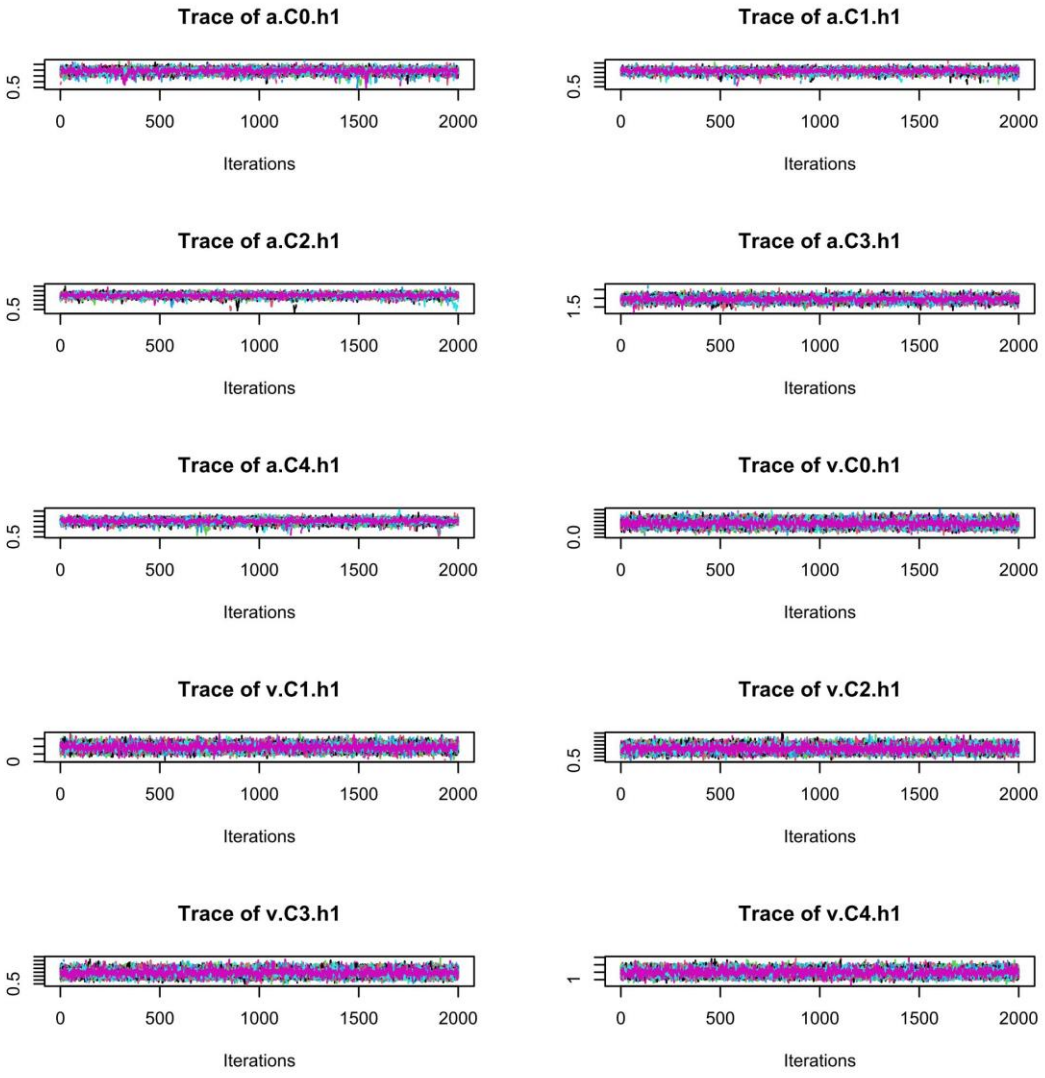
Appendices

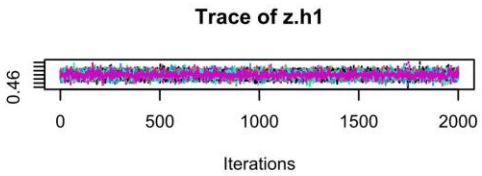
Appendix 1. Group parameters

Group parameters				
	2.5%	50%	97.5%	Rhat
a.C0.h1	1.586	1.936	2.249	1.001
a.C1.h1	1.772	2.145	2.488	1.001
a.C2.h1	1.691	2.021	2.324	1.002
a.C3.h1	1.711	1.959	2.205	1.001
a.C4.h1	1.677	2.030	2.353	1.001
v.C0.h1	1.088	1.761	2.484	1.001
v.C1.h1	1.121	1.854	2.636	1.001
v.C2.h1	1.282	1.981	2.798	1.001
v.C3.h1	1.195	1.918	2.700	1.001
v.C4.h1	1.226	1.987	2.803	1.001
z.h1	0.497	0.520	0.543	1.001
sv.C0.h1	0.006	0.122	0.280	1.001
sv.C1.h1	0.009	0.201	0.572	1.001
sv.C2.h1	0.008	0.163	0.417	1.001
sv.C3.h1	0.009	0.184	0.451	1.001
sv.C4.h1	0.006	0.121	0.288	1.001
sz.h1	0.011	0.131	0.216	1.001
t0.C0.h1	0.387	0.503	0.630	1.009
t0.C1.h1	0.347	0.449	0.533	1.013
t0.C2.h1	0.069	0.457	0.858	1.002
t0.C3.h1	0.310	0.451	0.551	1.010
t0.C4.h1	0.196	0.439	0.584	1.005
a.C0.h2	0.459	0.649	1.041	1.002
a.C1.h2	0.486	0.691	1.138	1.002
a.C2.h2	0.448	0.628	0.997	1.001
a.C3.h2	0.363	0.505	0.765	1.002
a.C4.h2	0.472	0.662	1.067	1.001
v.C0.h2	1.097	1.518	1.958	1
v.C1.h2	1.200	1.641	1.977	1.001
v.C2.h2	1.156	1.601	1.973	1.001
v.C3.h2	1.203	1.642	1.978	1.001
v.C4.h2	1.295	1.727	1.986	1.001
z.h2	0.035	0.048	0.070	1.001
sv.C0.h2	0.124	0.229	0.387	1.005
sv.C1.h2	0.350	0.595	1.218	1.001
sv.C2.h2	0.227	0.391	0.640	1.001
sv.C3.h2	0.238	0.410	0.684	1.002
sv.C4.h2	0.133	0.244	0.408	1.001
sz.h2	0.076	0.137	0.246	1.002
t0.C0.h2	0.118	0.169	0.780	1.020
t0.C1.h2	0.109	0.156	0.337	1.025
t0.C2.h2	0.152	0.284	1.834	1.007
t0.C3.h2	0.118	0.168	0.743	1.026
t0.C4.h2	0.122	0.183	1.275	1.013

Estimated parameters: threshold (a), drift (v), drift variability (sv), starting point (z), starting point variability (sz), non-decision time (t0). C0, C1, C2, C3 and C4 represent before, baseline, middle, end and after blocks. h1 stands for posterior location parameters and h2 for posterior scale parameters. Rhats represent Brooks and Gelman's R statistics.

Appendix 2. Markov chain Monte Carlo traces.




Trace of z.h1
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500
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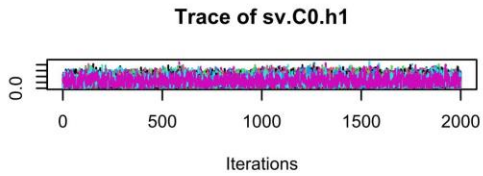
1500
2000
Iterations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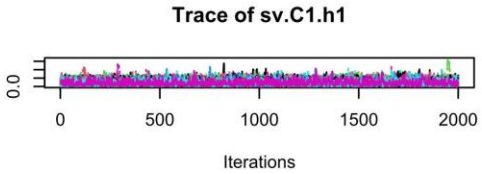
Iterations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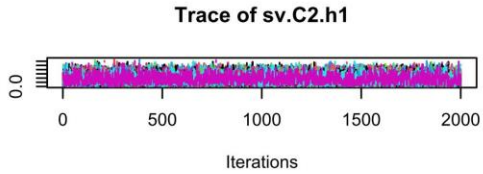
500
1000
1500
2000
Iterations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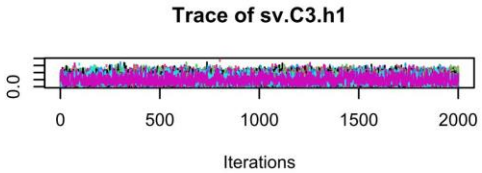
2000
Iterations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1000
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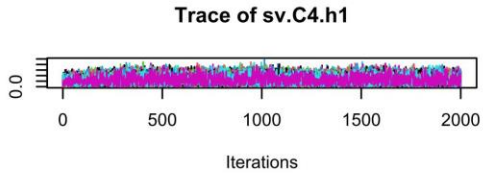
2000
Iterations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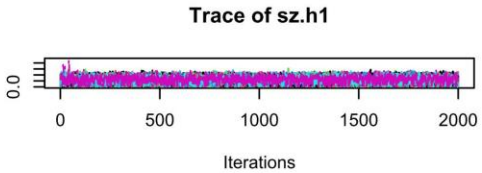
Iterations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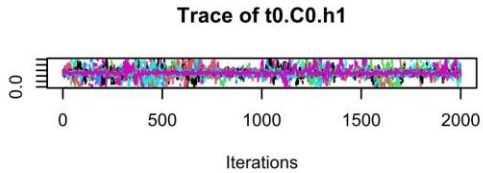
2000
Iterations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1000
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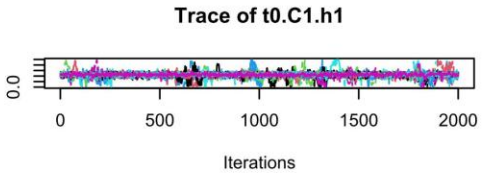
2000
Iterations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1000
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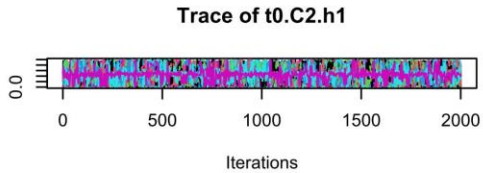
2000
Iterations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1000
1500
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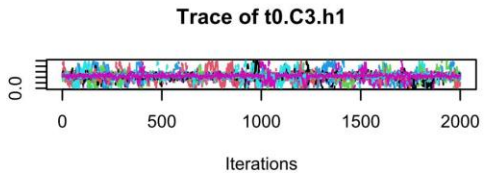
Iterations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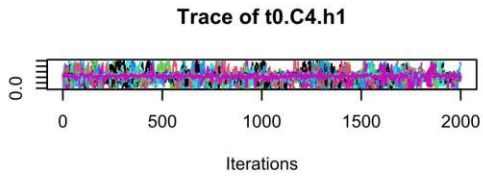
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1500
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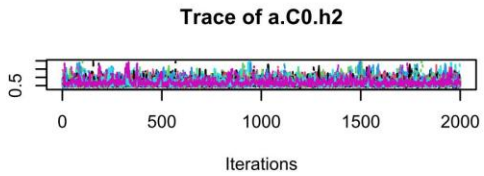
Iterations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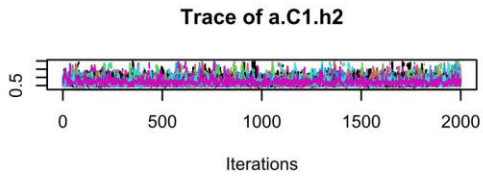
2000
Iterations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2000
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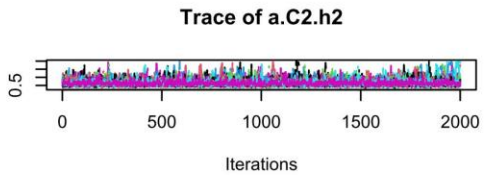
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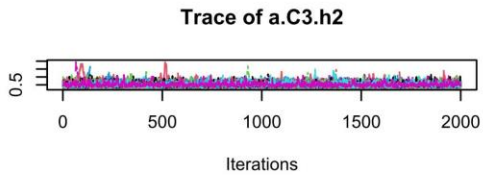
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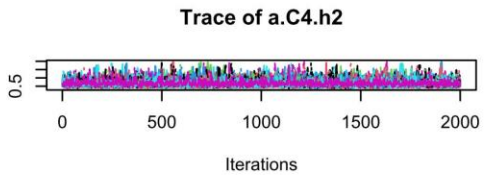
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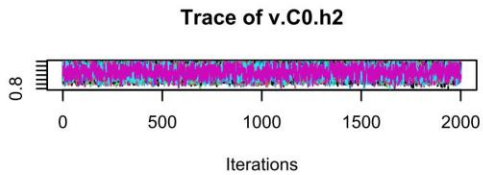
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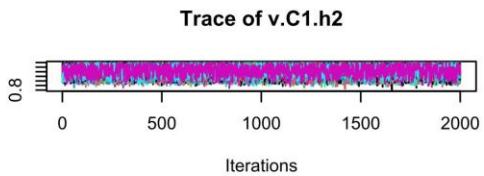
Iterations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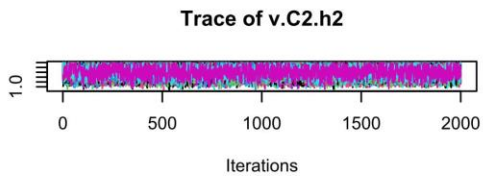
Iterations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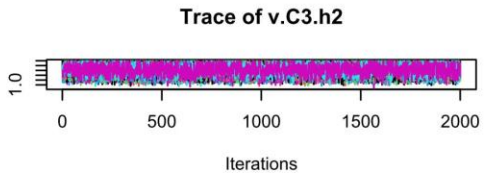
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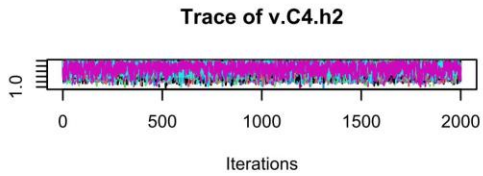
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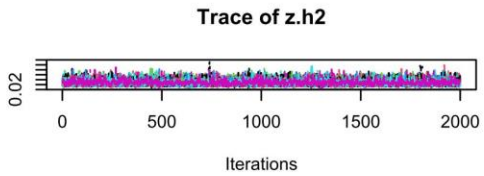
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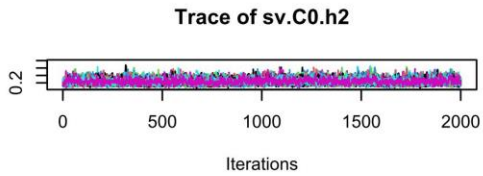
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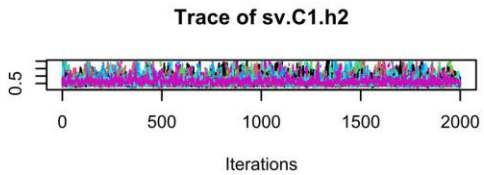
Iterations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1000
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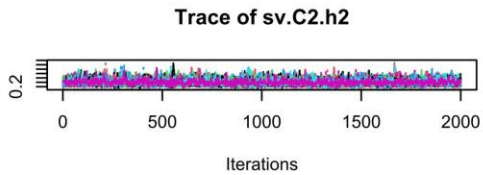
2000
Iterations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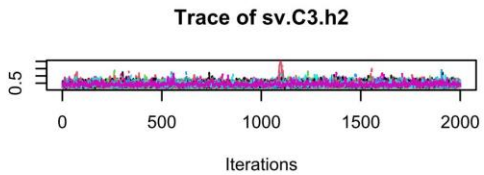
Iterations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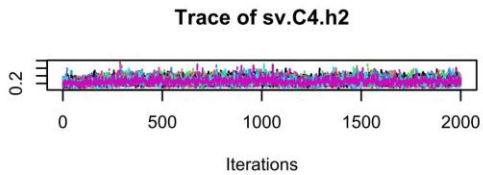
Iterations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1500
2000
Iterations

Trace of sz.h2
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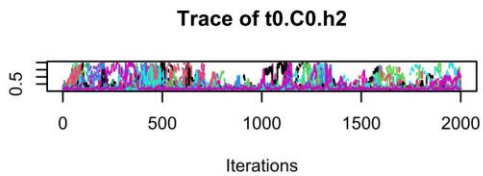
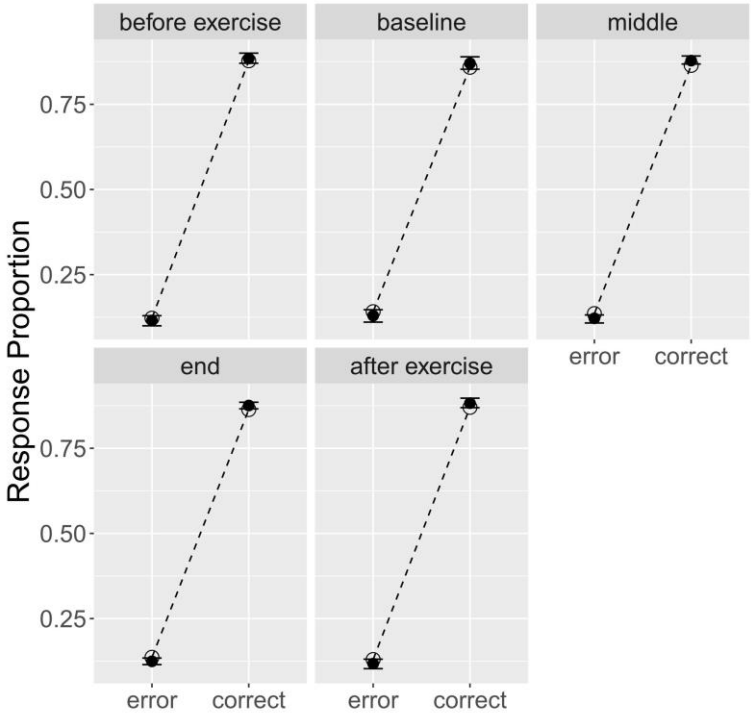
0
500
1000
1500
2000
Iterations


Trace of t0.C0.h2
0.5
0
500
1000
1500
2000
Iterations

Appendix 3. Model predictions.



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