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Higher inhibitory control is required to escape the innate attraction to effort minimization

Boris Cheval[a,b,*], Marcos Daou[c], Daniel A.R. Cabral[d], Mariane F.B. Bacelar[d], Juliana O. Parma[d], Cyril Forestier[e], Dan Orsholits[f], David Sander[a,b], Matthieu P. Boisgontier[g,h], Matthew W. Miller[d,i]

[a] Swiss Center for Affective Sciences, University of Geneva, Geneva, Switzerland
[b] Laboratory for the Study of Emotion Elicitation and Expression (E3Lab), Department of Psychology, FPSE, University of Geneva, Geneva, Switzerland
[c] Department of Kinesiology, Coastal Carolina University, USA
[d] School of Kinesiology, Auburn University, USA
[e] Univ. Grenoble Alpes, SENS laboratory, Grenoble, France
[f] Swiss NCCR "LIVES – Overcoming Vulnerability: Life Course Perspectives", University of Geneva, Switzerland
[g] School of Rehabilitation Sciences, Faculty of Health Sciences, University of Ottawa, Ottawa, ON, Canada
[h] Bruyère Research Institute, Ottawa, ON, Canada
[i] Center for Neuroscience, Auburn University, USA

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ABSTRACT

Recent evidence suggests humans have an automatic attraction to effort minimization. Yet, how this attraction is associated with response inhibition is still unclear. Here, we used go/no-go tasks to capture inhibitory control in response to stimuli depicting physical activity versus physical inactivity in 59 healthy young individuals. Higher commission errors (i.e., failure to refrain a response to a "no-go" stimulus) indicated lower inhibitory control. Based on the energetic cost minimization theory, we hypothesized that participants would exhibit higher commission errors when responding to physical inactivity stimuli rather than physical activity stimuli. Mixed effects models showed that, compared to physical activity stimuli, participants exhibited higher commission errors when responding to stimuli depicting physical inactivity (odds ratio = 1.59, 95% Confidence Interval = 1.18 to 2.16, $p = .003$). These results suggest that physical inactivity stimuli might require high response inhibition. This study lends support for the hypothesis that an attraction to effort minimization might affect inhibitory processes in the presence of stimuli related to this minimization. The study pre-registration form can be found at https://doi.org/10.17605/OSF.IO/RKYHB.

1. Introduction

Imagine you have planned to go to the gym after work. You go home to take your bag, but meanwhile the sofa has grabbed your attention and you cannot resist the temptation to throw yourself into it. Despite your best intention to be active, you prefer to go for a workout another day. Physical inactivity remains one of the leading risk factors for global mortality (Guthold, Stevens, Riley, & Bull, 2018; WHO, 2010). Each year, physical inactivity costs 67.5 billion international dollars (Ding et al., 2016) and is responsible for approximately 3.2 million deaths worldwide (WHO, 2010). So, why despite our intention to exercise, do we often fail to convert this intention into behavior? A recent theory suggests an answer to this question.

The theory of energetic cost minimization (Cheval, Radel, et al., 2018; Cheval, Sarrazin, Boisgontier, & Radel, 2017) contends that the inability to adopt regular physical activity behaviors could be explained by an automatic attraction toward behaviors minimizing energetic cost. This theory draws on an evolutionary perspective of physical activity (Lee, Emerson, & Williams, 2016; Lieberman, 2015; Speakman, 2019) as well as on a neuroscientific perspective of physical effort, which reveals a human tendency to behave in a way that maximizes reward and minimizes effort (Bernacer et al., 2019; Klein-Flügge, Kennerley, Friston, & Bestmann, 2016; Prévost, Pessiglione, Météreau, Cléry-Melin, & Dreher, 2010; Skvortsova, Palminteri, & Pessiglione, 2014).

* Corresponding author. Campus, Biotech, Chemin des mines 9, 1202, Genève, Switzerland.
E-mail address: boris.cheval@unige.ch (B. Cheval).

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Anchored within this theory, recent studies suggested that executive functions are critical in counteracting the automatic attraction to effort minimization (Cheval et al., 2020; Cheval et al., 2019; Cheval, Tipura, et al., 2018). For instance, epidemiological studies have shown that higher levels of cognitive functioning are associated with higher engagement in physical activity (Cheval, Orsholits, et al., 2020). These cognitive functions appear to have a protective effect, particularly when environmental conditions make the engagement on physical activity behaviors difficult (Cheval et al., 2019). In addition, an electroencephalography (EEG) study revealed that, compared with stimuli depicting physical activity, avoiding stimuli depicting sedentary behaviors is associated with higher conflict monitoring and higher response inhibition, with a particularly pronounced effect for inhibitory functions. These findings suggest that higher levels of inhibitory control are required to counteract a general tendency to avoid physical effort (Cheval, Radel, et al., 2018).

Many tasks have been developed to assess inhibitory functions, including the Stroop task, the stop-signal task, and the go/no-go task (Duckworth & Kern, 2011). The go/no-go task requires participants to quickly decide whether they should react to a stimulus or not. The participant must develop a prepotent motor response to a frequently appearing neutral "go" stimulus (e.g., press the space bar), while refraining from reacting to a less frequently appearing neutral "no-go" stimulus. Results from studies using a neutral go/no-go task to explain physical activity are inconclusive. One study observed that better performance (i.e., faster reaction times in go trials) on a go/no-go task was associated with higher self-reported physical activity behaviors (Hall, Fong, Epp, & Elias, 2008), whereas a more recent work did not observe such associations (Pfeffer & Strobach, 2017). However, these studies investigated general inhibitory functions rather than inhibitory functions specifically associated with physical activity behaviors.

To assess inhibitory control associated with a given behavior, go/no-go tasks in which neutral stimuli were replaced by stimuli relevant to the regulation of the specific behavior (e.g., stimuli depicting food or physical activity) have been developed (Carbine et al., 2017; Kullmann et al., 2014; Meule & Kübler, 2014). To the best of our knowledge, only one study has used a go/no-go task involving stimuli depicting physical activity and inactivity (Kullmann et al., 2014). Results showed that female patients with anorexia nervosa demonstrated higher commission errors (i.e., the failure to withhold the behavioral response in the no-go trials) for physical activity stimuli compared to physical inactivity stimuli. These findings suggest that physical activity stimuli might be associated with an increased demand on the inhibitory control system in patients with anorexia nervosa, a population with the large majority exercising excessively (Davis et al., 1997). In other words, patients who exercise excessively may have difficulty inhibiting responses related to physical activity, whereas healthy people, especially the most physically inactive, may have difficulty inhibiting responses related to physical inactivity.

The aim of the present study was to assess whether the nature of a stimulus depicting physical activity or physical inactivity affects inhibitory control. Healthy individuals were asked to complete go/no-go tasks that included stimuli depicting physical activity and physical inactivity behaviors. In addition, participants completed a neutral go/no-go task to assess general inhibitory functions. We used commission errors as an indicator of inhibitory control (Wessel, 2018). Based on the theory of energetic cost minimization (Cheval, Radel, et al., 2018; Cheval et al., 2017), we hypothesized that, compared to stimuli depicting physical activity, individuals should exhibit higher commission errors for stimuli depicting physical inactivity stimuli (H1). In addition, because individuals with higher levels of usual physical activity are more successful in avoiding physical inactivity, we hypothesized that, compared to individuals with lower levels of usual physical activity, individuals with higher levels of usual physical activity should demonstrate lower commission errors for stimuli depicting physical inactivity (vs. activity) (H2).

We also explored whether the type of stimulus affects reaction times on go trials. Reaction times in a go/no go task are considered an indicator of attentional bias – an increased reaction time is interpreted as reflecting increased and maintained attention toward salient stimuli, thus delaying the responses (Carbine et al., 2017; Eigsti et al., 2006; Meule & Kübler, 2014). In addition, because previous studies showed that individuals with higher levels of physical activity exhibit automatic reactions supporting physical activity behaviors, including attentional bias, affective reactions, and approach tendencies (Bluemke, Brand, Schweizer, & Kahlert, 2010; Calitri, Lowe, Eves, & Bennett, 2009; Cheval, Miller, et al., 2020; Cheval, Sarrazin, Isoard-Gautheur, Radel, & Friese, 2015; Conroy, Hyde, Doerksen, & Ribeiro, 2010; Oliver & Kemps, 2018), we also explored whether the usual level of physical activity moderated any effects of the type of stimuli on reaction times.

2. Methods

2.1. Participants and procedures

Sample size was estimated to ensure sufficient power (80%) to detect effects in participants' EEG, which were recorded and will be subject to future analysis. Details about this sample size estimation can be found in the study pre-registration at https://doi.org/10.17605/OSF.IO/RKYHB. To determine whether we had sufficient power to detect the behavioral effects of interest in the present analysis, we used G*Power 3.1.9.4 (Faul, Erdfelder, Lang, & Buchner, 2007) to calculate implied power for a repeated-measures (type of stimuli) ANOVA related to H1 and a repeated-measures ANOVA testing for a within-subject (type of stimuli) x between-subject (usual level of physical activity) interaction related to H2. We assumed a medium effect size ($f = .25$), set β/α ratio = 4, input our $N = 59$, set number of groups = 2 (lower usual level of physical activity and higher usual level of physical activity), set number of measurements = 3 (physical activity stimuli, physical inactivity stimuli, and neutral stimuli), assumed a correlation among repeated measures = .5, and assumed a nonsphericity correction $\varepsilon = 1$. Results of the power calculations indicated we had more than 95% power with $\alpha < 0.05$.

Fifty participants were recruited from the College of Education Research Participant Pool at Auburn University (USA) and ten were recruited by word-of-mouth. Participants recruited from the Research Participant Pool were offered course credit for their participation. To be included in the study, participants had to be willing to participate in a laboratory session. Participants were excluded if they: had a physical impairment making physical activity difficult; had a neurological impairment; or were color blind. A total of sixty students were recruited, but one participant's data were excluded due to an experimenter error during data collection.

Participants gave written consent prior to participation. To avoid potential discomfort associated with a forced change, participants were not asked to change their habits (e.g., eating, drinking, sleeping) prior to the experiment. However, they were asked to complete a questionnaire assessing some potential confounding variables (i.e., hunger, thirst, physical activity during the previous day and the current day, sleep pattern, caffeine and cigarette consumption). Participants were then seated in an experimental cubicle in front of a computer to complete two physical activity and one neutral go/no-go tasks that were randomly ordered between participants. Immediately afterwards, participants filled out a short questionnaire to assess their usual level of physical activity and some demographic variables (e.g., age and gender). The Auburn University institutional review board for research involving human subjects approved this research and informed consent process.

2.2. Measures

2.2.1. Go/no-go tasks

Two physical activity go/no-go tasks were used to measure response inhibition to stimuli depicting physical activity and physical inactivity

(Kullmann et al., 2014). In the physically inactive task, participants were asked to respond as quickly as possible when an image depicting physical activity was presented on the screen (“go $_{\text{physical activity}}$” trials) by pressing the response key on a keyboard (i.e., the space bar), and refrain from pressing the response key when an image depicting physical inactivity was presented on the screen (“no-go $_{\text{physical inactivity}}$” trials). In the physically active task, the rules were inverted – participants were asked to press the response key for an image depicting physical inactivity (“go $_{\text{physical inactivity}}$” trials) and to refrain from pressing the response key when an image depicting physical activity was presented on the screen (“no-go $_{\text{physical activity}}$” trials).

A neutral go/no-go task was used to assess individual differences in response inhibition. In this task, the stimuli depicting physical activity and physical inactivity were replaced by stimuli that included an animal or not. Half of the participants were asked to respond as quickly as possible when an image depicting an animal was presented on the screen (“go” trials) and refrain from pressing the response key when an image not depicting an animal was presented on the screen (“no-go” trials). For the other half of participants, the rules were inverted. The neutral go/no-go task provided the baseline inhibitory control response of each participant. Each task consisted of 208 trials, with 75% of the trials consisting of go trials and 25% of no-go trials. The random inter-stimulus interval varied between 1200 and 1400 ms. Stimuli were presented for 500 ms (Figure 1). These characteristics of the task were already applied to investigate inhibitory control to high- and low-calorie food stimuli (Carbine et al., 2017). Here, we used the same set of stimuli as in Kullmann et al. (2014). The stimuli depicting physical activity and physical inactivity were closely matched. Therefore, the only element that critically varied between the two types of stimuli was the level of energy expenditure of the displayed individual. Each task began with eight practice trials (six go trials and two no-go trials), during which the researcher monitored the participants' performance to ensure they understood the task. After the practice trials preceding the first task, the participant performed additional practice trials if they reported or exhibited confusion about the task (this was the case for one participant). The researcher did not monitor the participants' performance during the actual trials, but monitored their EEG recording instead. Participants were not given feedback on the computer monitor during practice or actual trials. Task order was randomized across participants.

Commission errors (i.e., the failure to withhold the behavioral response in the no-go trials) were used as primary outcome. Additionally, reaction times (i.e., the time elapsed between the appearance of the image on screen and participants' response) in “go” trials were used as a covariate in the main analysis (i.e., to properly control its confounding influence on commission errors), and as a dependent variable in the exploratory analyses. Finally, omission error (i.e., an absence of response on a “go” trial before the appearance of the subsequent stimulus on the screen) and reaction times in no-go trials (i.e., when participant incorrectly answers) were recorded for descriptive purposes. Responses below 200 ms (<1%) and above 1500 ms (<1%) were excluded.

2.2.2. Usual level of physical activity

The usual level of physical activity was measured using the short and self-administered version of the International Physical Activity Questionnaire (IPAQ; Craig et al., 2003). Physical activities of moderate-to-vigorous intensity were assessed on a usual week rather than in the last 7 days as in the original version of the IPAQ. The questions of the IPAQ used were related to physical activities participants do at work/school, as part of their house and yard work, to get from place to place, and in their spare time for recreation, exercise, or sport.

2.3. Statistical analysis

Commission errors and reaction times on all correct “go” trials from the corresponding task were analyzed using mixed effect models (MEM). The MEM approach decreases the risk of type-I error and permits a correct estimation of parameters with multiple cross-random effects, like the present study where participants are crossed with stimuli (Boisgontier & Cheval, 2016). Here, we built MEM using the LmerTest package of the R software and specified both participants and stimuli as random factors (Bates, Mächler, Bolker, & Walker, 2014; Kuznetsova, Brockhoff, & Christensen, 2015; R Core Team, 2017). To reduce

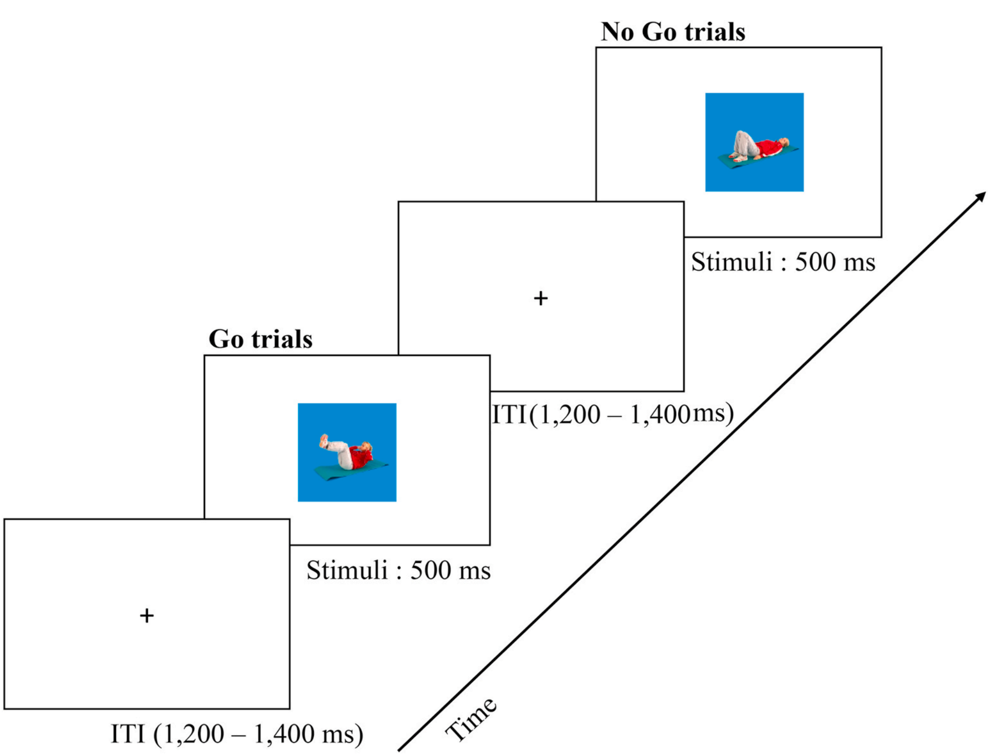

Fig. 1. Go/no-go tasks.
The experiment consisted of three go/no go tasks of 208 trials (go trials, 75% occurrence; no-go trials, 25% occurrence). In one task, participants were instructed to respond to physical activity images and to not respond to physical inactivity images (this task is depicted in the figure). In a second task, participants were instructed to respond to physical inactivity images and to not respond to physical activity images. In a third task, the stimuli depicting physical activity and physical inactivity were replaced by stimuli including an animal versus not including an animal (control task). Participants were either asked to respond to images depicting an animal and to not respond to images not depicting an animal, or to do the reverse. The order of tasks was randomized for each participant. The random inter-stimulus interval (ITI) varied between 1200 and 1400 ms. Stimuli were presented for 500 ms.

convergence issues, each model was first optimized using the default BOBYQA optimizer (Powell, 2009), the Nelder-Mead optimizer (Nelder & Mead, 1965), the nlimb optimizer from the optimx package (Nash & Varadhan, 2011), and then the L-BFGS-B optimizer (see Frossard & Renaud, 2019, for similar procedure). An estimate of the effect size was reported using the conditional pseudo R^2 computed using the MuMin package (Barton, 2018). Statistical assumptions associated with MEM were checked and met for all the models.

2.3.1. Commission errors

The association between the type of stimuli (physical activity vs. neutral vs. inactivity images) and the commission errors were analyzed using a logistic MEM. For each "no-go" trial, a failure to withhold the behavioral response was coded 1, whereas the correct inhibition of the behavioral response was coded 0. Higher commission errors could be influenced by a speed-accuracy trade-off. For example, participants responding more quickly to "go" trials in the "go $_{\text{physical activity}}$/no-go $_{\text{physical inactivity}}$" task than in the "go $_{\text{physical inactivity}}$/no-go $_{\text{physical activity}}$" task, are more likely to make commission errors in the former task simply because they are responding more quickly to it. Consequently, to determine whether the type of stimuli explains commission errors after accounting for the potential confounding influence of speed-accuracy trade-offs, we built a variable assessing each participant's median reaction times for the task in which the "no-go" stimuli were presented. That is, when the type of stimuli was physical inactivity, we controlled for median reaction time to physical activity stimuli; when the type of stimuli was physical activity, we controlled for median reaction time to physical inactivity stimuli; and when the type of stimuli was neutral, we controlled for median reaction time for neutral stimuli. We also examined whether this reaction time variable moderated the effect of the type of stimuli by including a Type of Stimuli x Reaction Time interaction variable.

Finally, to investigate the influence of the usual level of physical activity on commission errors, two-way interactions between the type of stimuli and the usual level of physical activity were included in the models. A moderating influence of the usual level of physical activity on commission errors would be evidenced by a significant interaction. To properly control for the confounding influence of the speed of response, a two-way interaction between median reaction times and usual level of physical activity was also added in the model.

2.3.2. Reaction times in the go trials

The association between the type of stimuli (physical activity vs. neutral vs. inactivity images) and reaction times (i.e., the time elapsed between the appearance of the stimulus on the screen and the participant's response) were analyzed using a linear MEM. Moreover, to investigate the influence of the usual level of physical activity on reaction times, two-way interactions between the type of stimuli and the usual level of physical activity were included in the models. A significant interaction would indicate that the usual level of physical activity moderated the effect of the type of stimuli on reaction times.

The p values for global effect of the type of stimuli were provided using likelihood ratio tests comparing models without and with the type of stimuli as fixed effects. The models tested with the usual level of physical activity were conducted on 52 participants only due to 7 participants reporting that they did not know how much time they spent in moderate to vigorous physical activity. Nevertheless, results of the models excluding participants with no information on physical activity were consistent with those of the main analyses.

2.4. Deviations from the pre-registered protocol

In the pre-registration, we stated that we would use behavioral responses as independent variables to explain physical activity (dependent variable). We changed this strategy to leverage the benefits of MEM (i.e., treating both participants and stimuli as random, avoiding having to average over observations, returning acceptable type I error rate), as well as to be consistent with the procedure adopted in previous studies (Cheval, Miller, et al., 2020; Cheval, Tipura, et al., 2018). Specifically, we used physical activity as a potential moderating variable of the effect of conditions on behavioral performance. In addition, in the pre-registration, we wrote that we would exclude participants with a low level of intention to be physically active (score < 5 on a 10-pt scale). We tested the models without six participants who met this exclusion criterion. In the pre-registration, we also stated that we would exclude participants taking psychotropic/illicit drugs. We tested the models without three participants who met this exclusion criterion. Results of these sensitivity analyses were consistent with those of the main analyses, both in terms of statistical significance and effect sizes, so we decided to include the participants who met the exclusion criteria.

3. Results

After the descriptive statistics, the results are reported in two sections: The first describes results of analyses on commission errors and the second describes results of the exploratory analyses on reaction times.

3.1. Descriptive statistics

Table 1 shows the characteristics of the participants. The final sample included 59 participants (32 women; mean age 21.6 ± 2.0 years). The usual level of moderate to vigorous physical activity was 551.9 min per week (±498.1 min). Commission error was of 12% for neutral stimuli, 23% for stimuli depicting physical activity, and 30% for stimuli depicting physical inactivity. Moreover, the mean reaction times to correctly go toward the stimuli were 428.0 ms for neutral stimuli, 491.7 ms for stimuli depicting physical activity, and 516.2 ms for stimuli depicting physical inactivity.

3.2. Commission error

3.2.1. Influence of the type of stimuli

The type of stimuli was associated with commission errors (p for global effect < .001). As hypothesized (H1), results showed that participants demonstrated higher commission errors for stimuli depicting physical inactivity compared with physical activity (odds ratio [OR] = 1.45, 95% Confidence Interval [95%CI] = 1.07 to 1.95, p = .015). Slower median reaction times were associated with lower commission

Table 1
Descriptive statistics.

N = 59		
Age (years) (mean: SD)	21.6	2.0
Gender (number; % women)	32	54.2
Intention to be active (Likert scale; 1–10) (mean; SD)	7.9	2.3
Usual level of MVPA (minutes) (mean; SD)	551.9	498.1
Commission errors (%; SD)		
Neutral stimuli	12	9
Physical activity stimuli	23	15
Physical inactivity stimuli	30	17
Mean reaction time (ms) for correct response to go trials (mean; SD)		
Neutral stimuli	428.0	47.9
Physical activity stimuli	491.7	74.4
Physical inactivity stimuli	516.2	95.2
Comission error (%; SD)		
Neutral stimuli	2	3
Physical activity stimuli	5	7
Physical inactivity stimuli	7	6
Mean reaction time (ms) for incorrect response to no-go trials (mean; SD)		
Neutral stimuli	398.2	95.2
Physical activity stimuli	476.2	89.3
Physical inactivity stimuli	481.8	87.3

Notes. SD = standard deviation; ms = milliseconds errors (OR = 0.67, 95%CI = 0.56 to 0.79, $p < .001$). However, median reaction time did not moderate the effect of the type of stimuli on commission errors (*ps* > .365), which suggested that the effect of the type of stimuli was not related to a speed-accuracy trade-off. The variables under consideration explained 27.4% of the variance in the commission errors (Table 2; Figure 2).

One participant had a high level of commission errors rates for both physical activity (98%) and physical inactivity related stimuli (93%). Models excluding this participant revealed similar results than those observed in the main analyses.

3.2.2. Moderating influence of the usual level of physical activity

The associations between the type of stimuli and commission errors were not moderated by the usual level of physical activity (*ps* > .639). Additionally, the effects of the type of stimuli on the commission errors remained unchanged after accounting for the usual level of physical activity (Table 2; Figure 2).

3.3. Reaction times for go trials

3.3.1. Influence of the type of stimuli

The type of stimuli was associated with reaction times in the go trials (*p* for global effect < .001). Results showed that participants were slower to go toward stimuli depicting physical inactivity compared with physical activity (b = 26.3, 95%CI = 11.5 to 41.0, $p = .001$). The variables under consideration explained 37.1% of the variance in the reaction times in the go trials (Table 2).

3.3.2. Moderating influence of the usual level of physical activity

The associations between the type of stimuli and the reaction times in the go trials were not moderated by the usual level of physical activity (*ps* > .245). Moreover, the effects of the type of stimuli on reaction times remained unchanged after accounting for the usual level of physical activity (Table 2).

4. Discussion

4.1. Main findings

This study investigated the response inhibition to stimuli depicting physical activity and physical inactivity in a sample of young healthy subjects. To assess inhibitory functions, we used a go/no-go task. Results revealed that, compared to stimuli depicting physical activity, participants exhibited higher commission errors (i.e., a failure to withhold the behavioral response) to stimuli depicting physical inactivity, thereby suggesting that physical inactivity stimuli may exert more demand on the inhibitory control system (Wessel, 2018). This effect was not moderated by the usual physical activity level. In other words, these findings may suggest that most individuals, irrespective of their usual level of physical activity, exhibit an innate attraction toward physical inactivity. However, more active individuals could be more effective at overcoming that attraction. Hence, our study lends support for the

Table 2
Results of the mixed models predicting commission error and reaction times in the go trials.

	Model: Commission error (n = 59)		Model: Commission error (n = 52)		Model: Reaction times in the go trials (ms) (n = 59)		Model: Reaction times in the go trials (ms) (n = 52)	
	OR (CI)	*p*	OR (CI)	*p*	b (CI)	*p*	b (CI)	*P*
Fixed Effects								
Intercept	0.27 (0.20; 0.37)	<.001	0.25 (0.18; 0.34)	<.001	489.6 (470.0; 509.2)	<.001	492.4 (471.0; 513.8)	<.001
Stimuli (ref. physical activity stimuli)								
Physical inactivity	1.45 (1.07; 1.95)	.015	1.50 (1.10; 2.04)	.010	26.3 (11.5; 41.0)	<.001	24.5 (9.4; 39.6)	.002
Neutral	0.33 (0.22; 0.50)	<.001	0.35 (0.23; 0.53)	<.001	−61.4 (−75.6;-47.1)	<.001	−63.2 (−78.6;-47.8)	<.001
Mean reaction time								
Participant's mean reaction time	0.67 (0.56; 0.79)	<.001	0.73 (0.60; 0.89)	.002				
Physical inactivity stimuli x Participant's median reaction time	1.08 (0.91; 1.29)	.407	1.04 (0.87; 1.25)	.639				
Neutral stimuli x Participant's median reaction time	1.17 (0.81; 1.69)	.365	1.09 (0.75; 1.58)	.641				
Usual level of physical activity								
Usual level of physical activity			1.11 (0.87; 1.41)	.395			−12.3 (−32.8; 8.2)	.245
Usual level of physical activity x Physical inactivity stimuli			1.02 (0.87; 1.20)	.812			−7.2 (−20.1; 5.7)	.281
Usual level of physical activity x Neutral stimuli			1.09 (0.82; 1.25)	.567			3.5 (−10.0; 17.0)	.615
Usual level of physical activity x Participant's median reaction time			1.08 (0.89; 1.32)	.440				
P Value for global effect	<.001				<.001			
Random Effects								
Participants								
Intercept	0.587		0.556		5286.0		5604.9	
Stimuli physical inactivity	0.09		0.09		2292.9		2106.0	
Stimuli neutral	0.460		0.501		2165.3		2303.7	
Corr. (Intercept, stimuli physical inactivity)	−0.17		−0.12		0.09		0.09	
Corr. (Intercept, stimuli neutral)	−0.56		−0.76		−0.78		−0.79	
Corr. (Stimuli physical inactivity; stimuli neutral)	0.55		0.48		0.27		0.28	
Stimuli								
Intercept	0.312		0.314		310.1		343.8	
Residual					11620.2		11707.6	
R^2	.274		.260		.371		.384	

Notes. CI = confidence interval at 95%

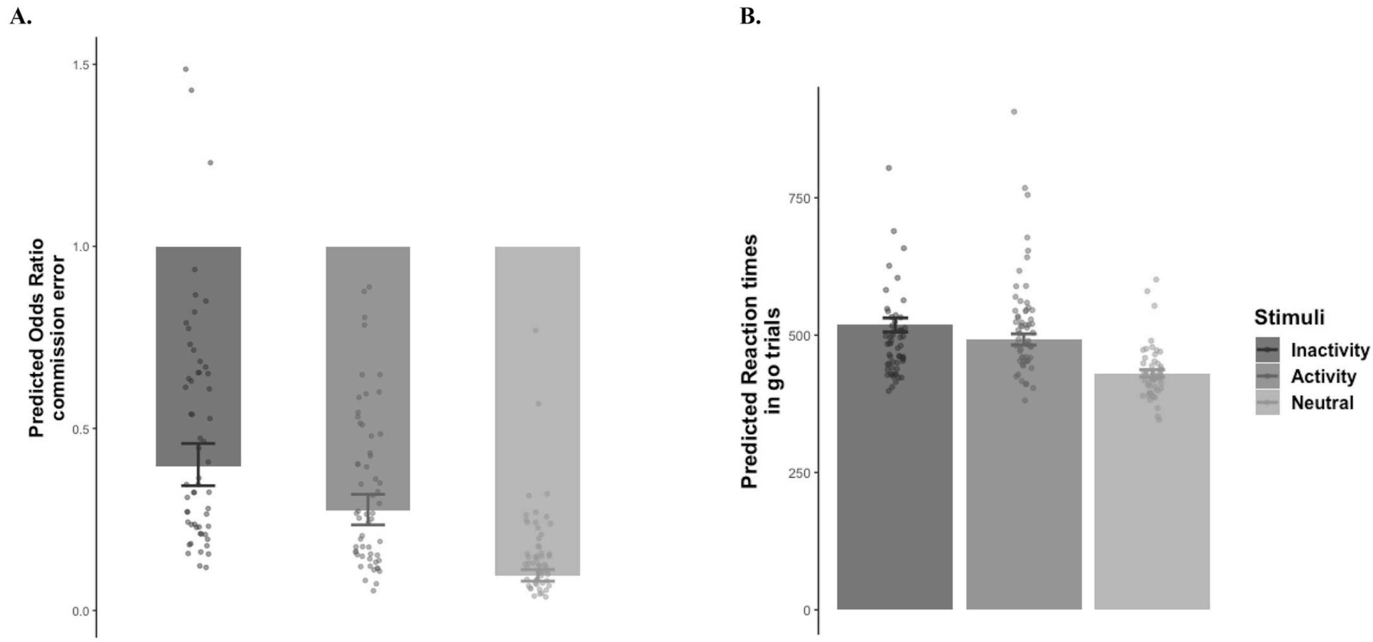

Fig. 2. Go/no-go outcomes. A. Commision error.
The odds ratio of a failure of inhibition in the no-go trials to stimuli depicting physical activity, neutral, and physical inactivity. **B. Reaction times in go trials.** The reaction times to go toward stimuli depicting physical activity, neutral, and physical inactivity.

theory of energetic cost minimization (Cheval, Radel, et al., 2018; Cheval et al., 2017) by revealing that higher levels of inhibitory control are required to withhold the behavioral tendency to approach behaviors minimizing energetic cost. These findings suggest that the ability to effectively resist sedentary temptations can play an essential role in the successful self-regulation of physical activity. Yet, it should be noted that other self-regulatory strategies can be used to proactively create situations without temptations that do not require the effortful inhibition of impulses (Duckworth, Gendler, & Gross, 2016). In the remainder of the discussion, we compare our results with other studies and then we consider the strengths and some limiting conditions of the findings.

4.2. Comparison with other studies

These findings are consistent with the recent EEG study that has shown that avoiding sedentary behaviors requires more cortical resources than avoiding physical activity behaviors (Cheval, Radel, et al., 2018). However, our study shows this effect using a task specifically designed to probe inhibitory control. This result also complements the observation that, in a pathological sample of individuals who tend to exercise excessively, physical activity stimuli are associated with an increased demand on the inhibitory control system when compared to physical inactivity stimuli (Kullmann et al., 2014). As such, the current findings suggest that the mechanisms underlying the regulation of response inhibition for physical activity and physical inactivity stimuli differ between a specific pathological population who tend to exercise excessively and a non-pathological sample.

Additionally, exploratory results showed that, compared with stimuli depicting physical activity, participants were slower to go toward stimuli depicting physical inactivity – slower reactions times reflecting attentional bias toward the stimulus depicted in the task (Carbine et al., 2017; Meule & Kübler, 2014). Therefore, this interpretation is consistent with the theory of energetic cost minimization's contention that behaviors minimizing energy cost are attractive. Moreover, another study contends that individuals with less ability to avoid temptations exhibit impaired inhibitory control on a neutral go/no-go task (Eigsti et al., 2006). In the present study, slower reaction times for physical inactivity stimuli relative to physical activity stimuli could indicate that the inactivity opportunities are perceived as temptations. This last interpretation is in line with previous studies arguing that behaviors minimizing energetic cost can reasonably act as temptations interfering with physical activity goals (Cheval et al., 2015; Cheval et al., 2017; Rouse, Ntoumanis, & Duda, 2013).

Nevertheless, an alternative explanation could be that faster reaction times for physical activity (vs. inactivity) stimuli may simply reflect an automatic tendency to approach physically active behaviors, as it has been inferred from reaction times in other paradigms such as the manikin task (De Houwer, Crombez, Baeyens, & Hermans, 2001). For example, previous studies revealed that the participants demonstrated a faster reaction time to approach (vs. avoid) physical activity stimuli and a faster reaction time to avoid (vs. approach) sedentary stimuli (Cheval et al., 2015; Cheval, Sarrazin, Isoard-Gautheur, Radel, & Friese, 2016; Cheval, Sarrazin, & Pelletier, 2014; Hannan, Moffitt, Neumann, & Kemps, 2019; Moffitt et al., 2019; Oliver & Kemps, 2018). Consistent with these results, one study showed that participants with anorexia nervosa, a disorder associated with excessive exercise, demonstrated faster reaction times to go toward physical activity (vs. physical inactivity) stimuli (Kullmann et al., 2014). Future studies assessing both approach-avoidance tendencies and response inhibition should allow the disentanglement between these two mechanisms. Alternatively, as stressed below in the limiting features of the current study, investigating the brain correlates associated with these reaction times differences could be useful to shed light on the underlying brain mechanisms mediating the behavioral outcomes showed herein.

4.3. Strengths and limiting conditions

Among the strengths of the present study are the investigation of inhibitory control in response to stimuli depicting physical activity and inactivity using go/no-go tasks specifically designed to probe inhibition response, the use of two different behavioral metrics measuring decision making (commission errors and reaction times in go trials), the proper control of the confounding influence of the speed-accuracy tradeoff (i.e., models testing commission errors accounted for the median reaction time), and the use of a statistical analysis suited to examine repeated-measures data involving cross-random factors (i.e., participants and stimuli).

However, this study includes four features that limit the conclusions that can be drawn. First, the pictures displayed a woman in sportswear in a sports context (i.e., mainly presented on a floor mat) being either in an active or inactive position. These characteristics could have made it harder to categorize physical inactivity stimuli as inactive than to categorize physical activity stimuli as active, which can explain the pattern of results observed for both the commission errors and reaction times. Therefore, the effects can be explained by inhibiting mechanisms but also by a difference in the speed of categorization between physical inactivity and physical activity stimuli. Moreover, the pictures were derived from a study investigating patients with anorexia nervosa, but were not formally validated in a non-pathological sample. Future studies should develop a set of images addressing this potential confound. Second, the usual level of physical activity was measured using a self-reported, although validated, questionnaire. Notably, since the questionnaire asked participants to report their usual level of physical activity, it may index participants' identity as an exerciser in addition to their usual level of physical activity. This feature limits the ability to evaluate how more direct and accurate measures of participants' usual physical activity level can influence the effects observed. Third, the present study involved individuals who were young, intended to be active, and self-reported as being highly active. These features limit the possibility to generalize the current results to other populations, such as older, non-intender, or inactive individuals. Fourth, our study investigated behavioral outcomes only, which did not allow light to be shed upon the neural mechanisms underlying commission errors and reaction times.

4.4. Conclusion

In conclusion, our study supports the suggestion that stimuli depicting physical inactivity (vs. physical activity) affects inhibitory control. Our findings are in line with the theory of energetic cost minimization (Cheval, Radel, et al., 2018; Cheval et al., 2017) by suggesting that, compared with physical activity stimuli, not going toward physical inactivity stimuli requires higher response inhibition. As such, if you struggle to follow your exercise plans at the time of picking up your sport bag at home, this could be explained by your inability to effectively inhibit the tempting sofa after a hard day of work.

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Ethical approval

This study was approved by the Auburn University Institutional Review Board (#19-173 EP 1905).

Consent to participate

All the participants agreed to participate and signed a written inform consent.

Consent for publication

All the authors listed in the by-line have agreed to the by-line order and to the submission of the manuscript in this form.

Availability of data and material

The dataset is available at https://zenodo.org/record/3237323#.XnB6Ey17RhE.

Code availability

The code is available at https://zenodo.org/record/3237323#.XnB6Ey17RhE.

CRediT authorship contribution statement

Boris Cheval: Formal analysis, Writing - original draft, Writing - review & editing. **Marcos Daou:** Data curation, Writing - review & editing. **Daniel A.R. Cabral:** Data curation, Formal analysis, Writing - review & editing. **Mariane F.B. Bacelar:** Formal analysis, Writing - review & editing. **Juliana O. Parma:** Formal analysis, Writing - review & editing. **Cyril Forestier:** Writing - review & editing. **Dan Orsholits:** Writing - review & editing. **David Sander:** Writing - review & editing. **Matthieu P. Boisgontier:** Writing - review & editing, Writing - original draft. **Matthew W. Miller:** Writing - review & editing, Formal analysis, Writing - original draft.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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