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Inhibitory Control Elicited by Physical Activity and Inactivity Stimuli: An Electroencephalography Study

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The theory of effort minimization in physical activity argues that individuals have an automatic attraction toward effort minimization. To engage in a physically active behavior, this automatic attraction needs to be overridden by controlled processes. However, direct evidence showing that inhibitory control is required to avoid effort minimization is lacking. Here, we used go/no-go tasks and electroencephalography to assess the neural correlates of inhibitory control associated with visual stimuli depicting physical inactivity or physical activity, or depicting control stimuli in 50 healthy young adults. The N2 event-related potential component amplitude was used as a physiological index of inhibitory control. Results showed significant two-way interactions between the type of trials (i.e., go vs. no-go trials) and the type of stimuli on N2, revealing a significantly more pronounced no-go effect (i.e., higher N2 in no-go relative to go trials) for control and physical inactivity stimuli compared with physical activity stimuli. Simple tests further revealed that N2 amplitude was more negative in no-go than go trials for control stimuli (b = –.91 μV, 95% CI = –1.42 to –.40 μV, $p < .001$) and for stimuli depicting physical inactivity (b = –.58 μV, 95% CI = –1.08 to –.08 μV, $p = .025$). By contrast, we found no evidence of significant differences in N2 amplitude between no-go and go trials for stimuli depicting physical activity (b = .20 μV, 95% CI = –.31 to .70 μV, $p = .445$). These findings suggest that inhibiting responses to physical inactivity stimuli requires significantly higher inhibitory control than inhibiting responses to physical activity stimuli.

Keywords: electroencephalography, response inhibition, go/no-go, energetic cost minimization, physical activity

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Physical inactivity is a widespread and consequential health issue, with over a quarter of the world's adults being physically inactive (Bull et al., 2020; Guthold et al., 2018), leading to approximately 5 million deaths (Lee et al., 2012; WHO, 2020) and costing 67.5 billion international dollars each year (Ding et al., 2016). Paradoxically, most people are aware that physical inactivity poses a serious threat to their health and intend to be physically active. For example, a survey of United States adults revealed that 89% believed physical inactivity to be a very important or somewhat important health risk (Martin et al., 2000). Likewise, a survey of Canadian adults showed that 94% have at least a moderate-to-strong intention to be physically active (Canadian Fitness and Lifestyle Research Institute, 2018). As people seem to be aware of the health consequences associated with physical inactivity and have the intention to be active, why do many individuals fail to translate this intention into action?

Based on a neuropsychological approach to physical effort (Bernacer et al., 2019; Klein-Flügge et al., 2016) anchored in an evolutionary perspective (Cheval, Radel, et al., 2018; Lee et al., 2016; Lieberman, 2015; Speakman, 2019), the recent theory of effort minimization in physical activity (TEMPA) proposes that an automatic attraction toward physical inactivity may explain this failure to engage in physical activity (Cheval & Boisgontier, 2021). The theory is supported by experimental evidence (see Cheval, Radel, et al., 2018 for a review) demonstrating that physically inactive opportunities can act as temptations interfering with physical activity goals (Cheval et al., 2017; Rouse et al., 2013). Additional evidence further suggested that a strong automatic approach tendency toward stimuli depicting physically inactive behaviors predicted lower engagement in a nonvolitional physical activity (i.e., spontaneous strength invested in a handheld dynamometer; Cheval et al., 2014) and explained why individuals intending to be physically active fail to turn this intention into action (Cheval et al., 2015).

If people are automatically attracted to physical inactivity, then cognitive resources may be of particular importance to counteract this attraction and may thereby favor engagement in physical activity. Epidemiological studies support this corollary of TEMPA (Cheval et al., 2019; Cheval, Orsholits, et al., 2020; Daly et al., 2015; Lindwall et al., 2012; Sabia et al., 2017; Snowden et al., 2011; Young et al., 2015). For example, older adults with more cognitive resources (e.g., higher delayed recall and verbal fluency performance) maintained physical activity during aging better than those with fewer resources (Cheval, Orsholits, et al., 2020). Besides epidemiological studies, experimental research has been conducted to examine people's spontaneous reactions toward visual stimuli depicting physical activity and physical inactivity, as these automatic reactions have been thought to explain people's engagement in physical activity (Cheval, Miller, et al., 2020; Conroy et al., 2010; Moffitt et al., 2019; Rebar et al., 2015). These experimental data suggest cognitive resources are important for avoiding physical inactivity stimuli (Cheval, Daou, et al., 2020; Cheval, Tipura, et al., 2018). For example, individuals exhibited greater brain activity associated with conflict monitoring and inhibitory control when avoiding physical inactivity stimuli, compared to physical activity stimuli in an approach-avoidance task (Cheval, Tipura, et al., 2018). Similarly, to more accurately assess response inhibition, Cheval, Daou, et al. (2020) had participants complete a go/no-go task wherein they were asked to avoid making a button-press response on trials with physical inactivity images (no-go trials) and to respond on trials with physical activity images (go trials) in an inhibit physical inactivity condition. Participants were asked to do the opposite in an inhibit physical activity condition. Results showed participants made more commission errors (i.e., failure to refrain a response to a "no-go" stimulus) in the inhibit physical inactivity condition, meaning participants were more likely to erroneously respond to a no-go trial if the image depicted physical inactivity, compared to physical activity (23% for stimuli depicting physical activity vs. 30% for stimuli depicting physical inactivity). This finding is consistent with the idea that inhibiting responses to physical inactivity stimuli taxed cognitive resources, specifically inhibitory control, to a greater extent than inhibiting responses to physical activity stimuli. This study also recorded participants' electroencephalography (EEG) while they performed the task to provide more direct evidence about whether withholding responses to physical inactivity stimuli requires greater inhibitory control. Thus, the analysis of EEG data will be the focus of the present article.

EEG can provide a physiological index of the inhibitory control demanded to avoid stimuli in go/no-go paradigms. The N2 component of the event-related potential (ERP) is the most common EEG measure used to gauge inhibitory control (Folstein & Van Petten, 2008). The N2 is a negative deflection in the ERP, usually seen 200–300 ms following stimulus onset and is maximal at frontocentral electrode sites. N2 amplitude is enhanced for stimuli that require overriding a prepotent response, which helped establish N2 as an index of inhibitory control. Notably, the N2 has been used to index the inhibitory control demanded in a go/no-go paradigm related to other health behaviors. Specifically, Carbine et al. (2017) had participants complete a go/no-go task wherein participants were asked to inhibit responses on trials with high-calorie (e.g., ice cream, hamburgers) images (no-go trials) and to respond on trials with low-calorie (e.g., broccoli, apples) images (go trials) in an inhibit high-calorie condition, and do the opposite in an inhibit low-calorie condition. Results showed the N2 was larger for no-go trials than go trials in the avoid high-calorie condition but not the avoid low-calorie condition, suggesting that withholding responses from high-calorie food images required higher inhibitory control than withholding responses from low-calorie food images.

The aim of the present study was to assess the neural mechanisms underlying the greater difficulty in withholding responses to physical inactivity stimuli compared with physical activity stimuli. Healthy young individuals completed a go/no-go task presenting physical activity and inactivity stimuli and a control condition presenting stimuli unrelated to physical activity and inactivity (Cheval, Daou, et al., 2020). The control condition was added to determine the directionality of the effects—that is, do physical inactivity stimuli required higher inhibitory control relative to control stimuli? Do physical activity stimuli required lower inhibitory control relative to control stimuli? Or both? However, as described in the discussion section, results associated with the control condition can hardly be used to accurately determine the directionality of the effects. We used N2 as an indicator of inhibitory control (Folstein & Van Petten, 2008). Based on the TEMPA (Cheval & Boisgontier, 2021; Cheval, Radel, et al., 2018); we hypothesized that, relative to inhibiting responses to physical activity stimuli, N2 should be higher when inhibiting responses to physical inactivity stimuli (i.e., higher demands on inhibitory control; H1). Moreover, because inhibitory

control is thought to play a key role in explaining individuals' ability to counteract the automatic attraction toward physical inactivity (Cheval, Orsholits, et al., 2020); we hypothesized that these cortical outcomes should be less pronounced when the usual level of physical activity increases (H2). Finally, we repeated all analyses using the recently established, but less widely used, frontal midline theta (FMθ) EEG measure as a secondary outcome variable. FMθ reflects neuronal oscillations between 4 and 8 Hz recorded at frontocentral electrode sites and its power increases when inhibitory control is required, such as when overriding a prepotent response (Cavanagh & Frank, 2014). Similar to the N2, FMθ has been used to index inhibitory control demanded in a go/no-go paradigm related to food stimuli (van de Vijver et al., 2018). As such, consistent with the N2 hypotheses, we predicted that participants should exhibit greater FMθ when inhibiting responses to physical inactivity stimuli compared with physical activity stimuli (H3), and that these effects should be moderated by participants' usual physical activity level (H4).

Method

Study preregistration, materials, data, and statistical analysis scripts can be found at https://doi.org/10.17605/OSF.IO/RKYHB (Miller et al., 2020).

Participants

Sample size was determined with a power calculation using G*Power 3.1.9.2 (Faul et al., 2007). We used the ANOVA: repeated-measures, within factors statistical test; set $\alpha = .05$ and $1-\beta = .95$; set groups = 1; set measures = 2: (1) trial (go/no-go) and (2) condition (inhibit physical activity/inhibit physical inactivity); and set nonsphericity $\epsilon = 1$. We based our effect size on Carbine et al. (2017) given the similarities between their study and ours (e.g., both studies used a go/no-go paradigm wherein participants had to inhibit stimuli related to health-related behaviors and used N2 amplitude as the dependent variable). Carbine et al., reported a Condition × Trial interaction with $\eta_p^2 = .26$, which we rounded down to .20. The power calculation estimated a required $N = 55$, which we rounded up to 60 to account for lost data (e.g., due to poor EEG recording).

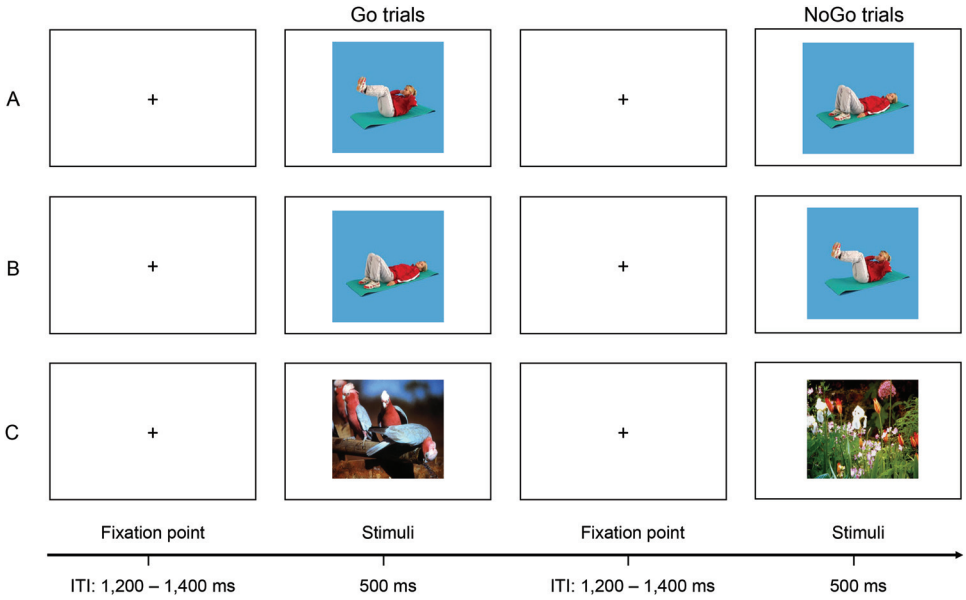
Participants, who were the same as for the behavioral study (Cheval, Daou, et al., 2020), were recruited via the Auburn University (U.S.) College of Education SONA participant recruitment system and by word-of-mouth. To sign up for the study, participants had to be 19–30 years old and free from (1) physical impairment that makes physical activity difficult; (2) color blindness; (3) sensitivity/allergies to lotions or cosmetics; and (4) neurological impairment. Participants were offered course credit for their participation when possible. Participants were excluded if they had a history of psychiatric, neurological, or severe mental disorders, or were taking psychotropic medication or illicit drugs at the time of the study. This led to the removal of three participants. We also excluded five participants with a weak intention to be physically active (score < 5 on a 10-point scale asking about physical activity intentions) because we were interested in examining whether an automatic attraction toward physical inactivity demands inhibitory control in people who intend to be physically active, who constitute the majority of the population (Canadian Fitness and Lifestyle Research Institute, 2018; Martin et al., 2000). Two additional participants were removed due to problems with data collection. Thus, the final sample was $N = 50$, resulting in a power of 94%, keeping the other inputs constant in the power calculation (Faul et al., 2007).

Procedures

Participants gave written consent to a protocol approved by Auburn University's institutional review board. Then, they completed a questionnaire about some potential confounding variables (i.e., hunger, thirst, physical activity during the previous day and the current day, sleep pattern, as well as caffeine and cigarette consumption). Next, participants were prepared for EEG, which was collected from a BrainVision actiCAP system (Brain Products GmbH, Munich, Germany) labeled in accord with an extended international 10–20 system (Oostenveld & Praamstra, 2001) and sampled at 250 Hz. The EEG signal was referenced online to the left earlobe, and a common ground was employed at the FPz electrode site. Electrode impedances were maintained below 25 kΩ throughout the study, and a high-pass filter was set at .016 Hz. A BrainAmp DC amplifier (Brain Products GmbH) amplified and digitized the signal, which was recorded on a computer running BrainVision Recorder software (Brain Products GmbH). Participants were then seated 75 cm from the center of a 48 cm computer monitor and given instructions to facilitate EEG recording (e.g., avoid movement other than making required task responses).

Participants then completed the go/no-go task, which consisted of inhibit physical inactivity and inhibit physical activity conditions that used images from Kullmann et al., (2014). Stimuli depicted a model engaging in physical activity or inactivity, and the images were matched so that the only element that varied between them was the level of energy expenditure displayed by the model. As a control condition, a go/no-go condition used stimuli unrelated to physical activity and inactivity from the International Affective Picture System, half of which contained animals and the other half of which did not, and the images were matched based on past ratings of valence, arousal, and dominance (Lang et al., 2008). Specifically, images that included an animal had a valence of 6.34 (±1.35), an arousal of 4.30 (±.89), and a dominance of 5.79 (±.76) on a 9-point scale. Images without an animal had a valence of 6.32 (±.93), an arousal of 4.17 (±.97), and a dominance of 5.79 (±.76) (see Supplemental Table 1). Condition order was randomized across participants. In the inhibit physical inactivity condition, 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 to not press the response key when an image depicting physical inactivity was presented on the screen ("no-go $_{\text{physical inactivity}}$" trials). In the inhibit physical activity condition, the instructions were reversed—participants were asked to press the response key for an image depicting physical inactivity ("go $_{\text{physical inactivity}}$" trials) and to not press the response key when an image depicting physical activity was presented on the screen ("no-go $_{\text{physical activity}}$" trials). In the control condition, the images depicting physical activity and physical inactivity were replaced by the ones 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 to not press the response key when an image not depicting an animal was presented on the screen ("no-go" trials). For the other half of

Figure 1
Go/No-Go Tasks



Note. The experiment consisted of three go/no-go conditions of 208 trials (go trials, 75% occurrence; no-go trials, 25% occurrence). A. Avoid physical inactivity condition. In this condition, participants were instructed to respond to physical activity images and to not respond to physical inactivity images. B. Avoid physical activity condition. In this condition, participants were instructed to respond to physical inactivity images and to not respond to physical activity images. C. Control condition. In this third condition, the stimuli depicting physical activity and physical inactivity were replaced by stimuli including an animal versus not including an animal (control condition). Participants were either asked to respond to images depicting an animal and to not respond to images not depicting an animal (this condition is depicted in the figure), or to do the reverse. The order of conditions was randomized for each participant. The random intertrial interval varied between 1,200 and 1,400 ms. Stimuli were presented for 500 ms. See the online article for the color version of this figure.

participants, the instructions were reversed. Each condition had 208 trials, 75% of which were go trials and 25% of which were no-go trials. Each trial began with an image presented for 500 ms followed by an intertrial interval that randomly varied between 1200 and 1400 ms and during which a fixation cross was presented (see Figure 1). The trial structure and go to no-go trial ratio in each condition was based on Carbine et al. (2017).[1] Each condition 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 condition, the participant performed additional practice trials if they reported or exhibited confusion about the task (this was the case for one participant). After the practice trials preceding any condition, the experimenter reinforced instructions to the participant if they reported or exhibited confusion about the task.

After the final condition, participants completed a questionnaire assessing their personality and demographic characteristics, attitudes/intentions toward exercise, and usual physical activity behavior. Usual physical activity was measured with a short, self-administered version of the International Physical Activity Questionnaire (Craig et al., 2003), which asked participants to indicate how much moderate-to-vigorous physical activity they do during a usual week, as part of their everyday lives.

EEG Data Processing

EEG data processing was conducted with BrainVision Analyzer 2.2 software (Brain Products GmbH, Munich, Germany). Data were visually inspected, and malfunctioning electrodes were spherically interpolated, after which data were rereferenced to an average of the left and right ears. Next, data were prepared for independent component analysis (ICA) by applying an IIR 1–30 Hz bandpass filter with 4th order roll-offs and 60 Hz notch filter. Then data exhibiting nonstereotypical artifact (e.g., nonocular-related artifact) and data recorded between conditions were marked for exclusion from the ICA, which was run to identify components reflecting stereotypical artifacts (e.g., blinks and saccades). These components were then removed from the rereferenced, unfiltered

[1] We wanted to present all 26 of Kullmann et al.'s images equally in go and no-go conditions, so we increased the number of trials from 200 to 208, which is a factor of 26, and decreased the percentage of no-go trials from 30% to 25%, to allow each image to be presented two times in a no-go condition and six times in a go condition. These slight modifications worked to our advantage by increasing our number trials and, thus, signal-to-noise ratio, and decreasing the likelihood of a trial being a no-go trial, thereby possibly increasing demands on inhibitory control.

data, which were then submitted to an IIR .1–30 Hz bandpass filter with 4th order roll-offs and 60 Hz notch filter.

For the ERP (N2) analysis, data were segmented into epochs beginning 200 ms before and ending 1000 ms after image onset. Epochs were baseline corrected using the mean of the 200 ms period before image onset and then submitted to an automatic artifact rejection that removed epochs with $>$ 50 μV/ms step, $>$100 μV change in a sliding 200 ms window, or $<$ .5 μV change in a sliding 200 ms window at a midline electrode (Fz, FCz, Cz, or Pz). This led to an average of 98.9% of 624 trials being retained per participant (minimum trials retained for a participant = 536 [85.9% of trials]). N2 was quantified as mean amplitude 200–300 ms after image onset, averaged across electrodes FCz and Cz, based on Carbine et al. (2017); and extreme values ($<$ –50 μV or $>$ +50 μV) were deleted ($<$.01% trials were removed), based on past work from our lab (Lohse et al., 2020). We kept trials wherein participants made commission or omission errors, consistent with Carbine et al. (2017). Consequently, the median number of trials per condition was as follows: control go = 156 (minimum = 77); control no-go = 52 (minimum = 25); physical activity go = 156 (minimum = 133); physical activity no-go = 52 (minimum = 46); physical inactivity go = 156 (minimum = 128); and physical inactivity no-go = 52 (minimum = 43).

For the FMθ analysis, data were segmented into epochs beginning 500 ms before and ending 1000 ms after image onset. Epochs were then submitted to an automatic artifact rejection that removed epochs with $>$ 50 μV/ms step, $>$100 μV change in a sliding 200 ms window, or $<$ .5 μV change in a sliding 200 ms window at a midline electrode (Fz, FCz, Cz, or Pz). This led to an average of 98.7% of 624 trials being retained per participant (minimum trials retained for a participant = 532 [85.3% of trials]). Next, epochs were convolved with a 3-cycle complex Morlet wavelet consisting of 20 frequencies between 1 and 40 Hz that increased logarithmically and was normalized with a *z*-transformation referenced to an interval 500–200 ms before image onset. For each participant, the wavelet between 3.206 and 6.969 Hz that exhibited the greatest peak power 300–700 ms after image onset at electrode FCz was identified, and mean power between 300 and 700 ms at electrode FCz was calculated, based on van de Vijver et al. (2018). Prior to statistical analyses, we visually inspected density plots and observed 99% of values fell between -30 μV^2 and $+41$ μV^2, but the full set of values ranged from -558 to 421 μV^2. To reduce the influence of these outlying scores, we excluded trials with values $<$ -50 μV^2 or $>$ $+50$ μV^2, as we did for the N2. We kept trials wherein participants made commission or omission errors, as we did for the N2. Consequently, the median number of trials per condition was the following: control go = 156 (minimum = 77); control no-go = 52 (minimum = 25); physical activity go = 156 (minimum = 133); physical activity no-go = 52 (minimum = 46); physical inactivity go = 156 (minimum = 127); and physical inactivity no-go = 52 (minimum = 41).

Statistical Analysis

Behavioral (i.e., commission errors) and EEG (i.e., N2 and FMθ) outcomes were tested using mixed effect models (MEM). MEM allow a correct estimation of parameters with multiple cross-random effects, such as in the present study, in which participants are crossed with stimuli. MEM can also decrease the risk of type-I error (Boisgontier & Cheval, 2016). All the analyses were conducted in R with the lme4 and lmerTest packages (Bates et al., 2014; Kuznetsova et al., 2015; R Core Team, 2017). To reduce convergence issues, each model was first optimized using the default BOBYQA optimizer (Powell, 2009), followed by 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).

For commission errors, the model used has been described in detail elsewhere (Cheval, Daou, et al., 2020). In short, we used a logistic MEM to assess the association between the type of stimuli (physical inactivity vs. physical activity vs. control stimuli) and the commission errors, adjusting for the potential confounding influence of speed-accuracy trade-offs (i.e., median reaction time (RT) for the opposite stimuli in each go/no-go condition). Moreover, to investigate the influence of usual level of physical activity on commission errors, two-way interactions between the type of stimuli and the usual level of physical activity were added to the previous model. A significant interaction would indicate that the usual level of physical activity moderated the effect of the type of stimuli on commission errors.

For EEG outcomes (i.e., N2 and FMθ), we used linear MEM that included the type of trials (i.e., go vs. no-go trials), the type of stimuli (physical inactivity vs. physical activity vs. control stimuli), as well as their interaction as fixed factors. The MEM specified both participants and stimuli as random factors, and included random effects for the type of stimuli and for the type of trials. Moreover, to investigate the influence of usual level of physical activity on the EEG outcomes, three-way interactions between the type of trials, the type of stimuli, and the usual level of physical activity were included in the models[2]. A moderating influence of the usual level of physical activity on the EEG outcomes would be evidenced by significant three-way or two-way interactions.

Estimates of the effect size were reported using the conditional pseudo R^2 computed using the MuMin package (Barton, 2018). Regions of significance were estimated using the interactions package in R (Long, 2019). Statistical assumptions associated with MEM (i.e., normality of the residuals, linearity, multicollinearity, and undue influence) were checked and were met for all models. For EEG outcomes, reliability (dependability) estimates of each of the six conditions of the go/no-go task were obtained using generalizability theory (Carbine et al., 2021; Clayson & Miller, 2017b), and using the ERP reliability analysis toolbox implemented in Matlab software (Clayson & Miller, 2017a, 2017b).

Results

After the descriptive statistics, the results are reported in three sections: The first describes results of analyses on commission errors, the second describes results of analyses on N2, and the third describes results of analyses on FMθ.

[2] In the pre-registration, we indicated that we would use N2/FMθ as independent variables to explain usual 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 Cheval et al. (2020). Specifically, we used usual physical activity as a potential moderating variable of the effect of type of trial and stimuli on N2/FMθ.

Descriptive Statistics

Table 1 shows participants' characteristics. The final sample included 50 participants (28 women; *M* age = 21.6 ±2.2 years). The usual level of moderate-to-vigorous physical activity was 559.5 min per week (±480.3 min). Commission error rate was 29% for stimuli depicting physical inactivity, 22% for stimuli depicting physical activity, and 14% for control stimuli. Differences in N2 amplitudes between the no-go and go trials (no-go minus go trials) were –.58 μV for physical inactivity stimuli, +.20 μV for physical activity stimuli, and –.94 μV for control stimuli. Finally, differences in FMθ amplitudes between no-go and go trials (no-go minus go trials) were +2.33 μV^2 for physical inactivity stimuli, +2.37 μV^2 for physical activity stimuli, and +3.06 μV^2 for control stimuli. Reliability estimates for the internal consistency of each of the six conditions of the go/no-go task were ≥.84 for the N2 outcome, which exceeds the suggested threshold (.80) in most ERP research contexts (Clayson & Miller, 2017b), thus demonstrating the reliability of the primary dependent variable. Using the internal consistency threshold recommended for exploratory ERP research (.70), four of the six FMθ outcomes met or exceeded the threshold, with no-go toward control and physical activity stimuli falling below the threshold at .62 and .56, respectively.

Commission Errors

The type of stimuli was associated with commission errors (*p* for global effect <.001). Compared with stimuli depicting physical activity, participants demonstrated higher commission errors for stimuli depicting physical inactivity (odds ratio [*OR*] = 1.50, 95% Confidence Interval [95% CI] = 1.11 to 2.01, $p = .007$), but lower commission errors for control stimuli (*OR* = .34, 95% CI = .24 to .50, $p < .001$). Slower median reaction times were associated with lower commission errors (*OR* = .72, 95% CI = .61 to .84, $p < .001$). However, median RT did not moderate the effect of the type of stimuli on commission errors (*p*s > .318), suggesting that the effect of the type of stimuli was not related to a speed–accuracy trade-off (see Cheval et al., 2020 for further explanation). The variables under consideration explained 23.5% of the variance in the commission errors (Table 2; Figure 2). The associations between the type of stimuli and commission errors were not moderated by the usual level of physical activity (*p*s > .110).

N2

Figure 3A shows grand average ERPs as a function of type of trial and stimuli as well as the N2 scalp distribution averaged

Table 1
Descriptive Statistics

Variables	*M*	*SD*	Reliability 95% CI
Age (years)	21.6	2.2	
Gender (number; % women)	28	56.0%	
Intention to be active (Likert scale; 1–10)	8.5	1.7	
Usual level of MVPA (minutes)	559.5	480.3	
Number commission errors (% of errors; *SD*)			
Control stimuli	16%	20%	
Physical activity stimuli	24%	16%	
Physical inactivity stimuli	31%	18%	
N2 ERP (μV)			
Go trials			
Control stimuli	−5.17	3.70	.95 [.94, .97]
Physical activity stimuli	−4.14	3.27	.94 [.92, .96]
Physical inactivity stimuli	−3.76	3.16	.95 [.93, .96]
No-go trials			
Control stimuli	−6.11	4.19	.90 [.86, .94]
Physical activity stimuli	−3.94	3.67	.86 [.81, .91]
Physical inactivity stimuli	−4.34	3.14	.84 [.78, .90]
Relative difference between no-go and go trials (no-go minus go trials)			
Control stimuli	−0.94		
Physical activity stimuli	0.20		
Physical inactivity stimuli	−0.58		
FMθ (μV^2)			
Go trials			
Control stimuli	4.55	1.46	.76 [.66, .84]
Physical activity stimuli	4.78	1.70	.77 [.67, .85]
Physical inactivity stimuli	4.86	1.76	.70 [.58, .80]
No-go trials			
Control stimuli	7.61	3.79	.62 [.47, .75]
Physical activity stimuli	7.15	3.17	.56 [.38, .71]
Physical inactivity stimuli	7.19	3.12	.73 [.61, .82]
Relative difference between no-go and go trials (no-go minus go trials)			
Control stimuli	3.06		
Physical activity stimuli	2.37		
Physical inactivity stimuli	2.33		

Note. Participants, *N* = 50. *M* = mean; *SD* = standard deviation; ms = milliseconds; MVPA = moderate-to-vigorous physical activity; 95% CI = 95% credible intervals; Reliability (dependability) analyses were estimated using generalizability theory.

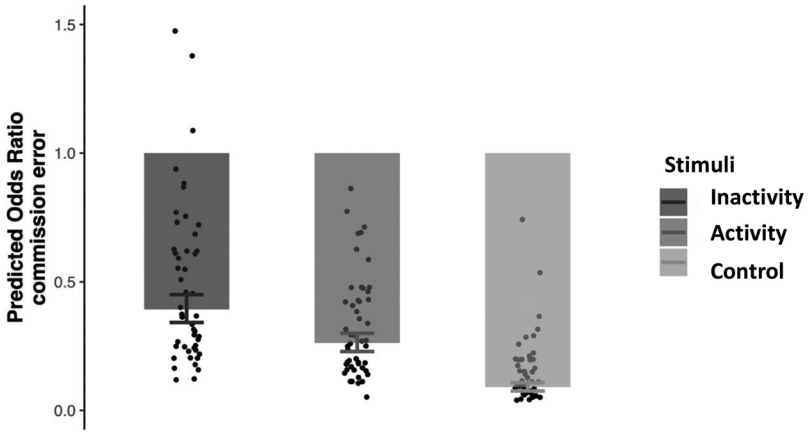
Table 2
Results of the Mixed Models Predicting Commission Errors

Commission error	Without MVPA* (n = 49)		With MVPA** (n = 42)	
	OR (CI)	*p*	*OR* (CI)	*p*
Fixed effects				
Intercept	0.26 (0.20, .34)	<.001	0.39 (0.30, 0.51)	<.001
Stimuli (ref. physical activity stimuli)				
Physical inactivity	1.50 (1.11, 2.01)	.007	1.56 (1.15, 2.13)	.004
Control	0.34 (0.24, 0.50)	<.001	0.36 (0.24, 0.53)	<.001
Median reaction time				
Median reaction time	0.72 (0.61, 0.84)	<.001	0.78 (0.65, 0.92)	.003
Physical Inactivity Stimuli × Median Reaction Time	1.10 (0.91, 1.34)	.318	1.06 (0.87, 1.30)	.553
Control Stimuli × Median Reaction Time	1.03 (0.73, 1.47)	.855	0.93 (0.65, 1.33)	.690
Usual level of physical activity				
Usual level of physical activity			1.02 (0.84, 1.24)	.816
Usual Level of Physical Activity × Physical Inactivity Stimuli			1.00 (0.83, 1.21)	.960
Usual Level of Physical Activity × Control Stimuli			1.21 (0.96, 1.54)	.110
*p-v*alue for global effect	<.001			
Random effects				
Participants				
Intercept	0.308		0.208	
Stimuli physical inactivity	0.119		0.095	
Stimuli control	0.118		0.280	
Corr. (Intercept, stimuli physical inactivity)	0.04		0.34	
Corr. (Intercept, stimuli control)	0.09		−0.33	
Corr. (Stimuli physical inactivity; stimuli control)	0.82		0.72	
Stimuli				
Intercept	0.274		0.278	
Residual				
R^2	.235		.213	

Note. *OR* = odd ratio; CI = confidence interval at 95%; MVPA = moderate-to-vigorous physical activity.
* The behavioral data file for one participant was lost, reducing the sample size by one. ** With MVPA the final sample size is n = 42, because 7 participants did not report their usual physical activity level.

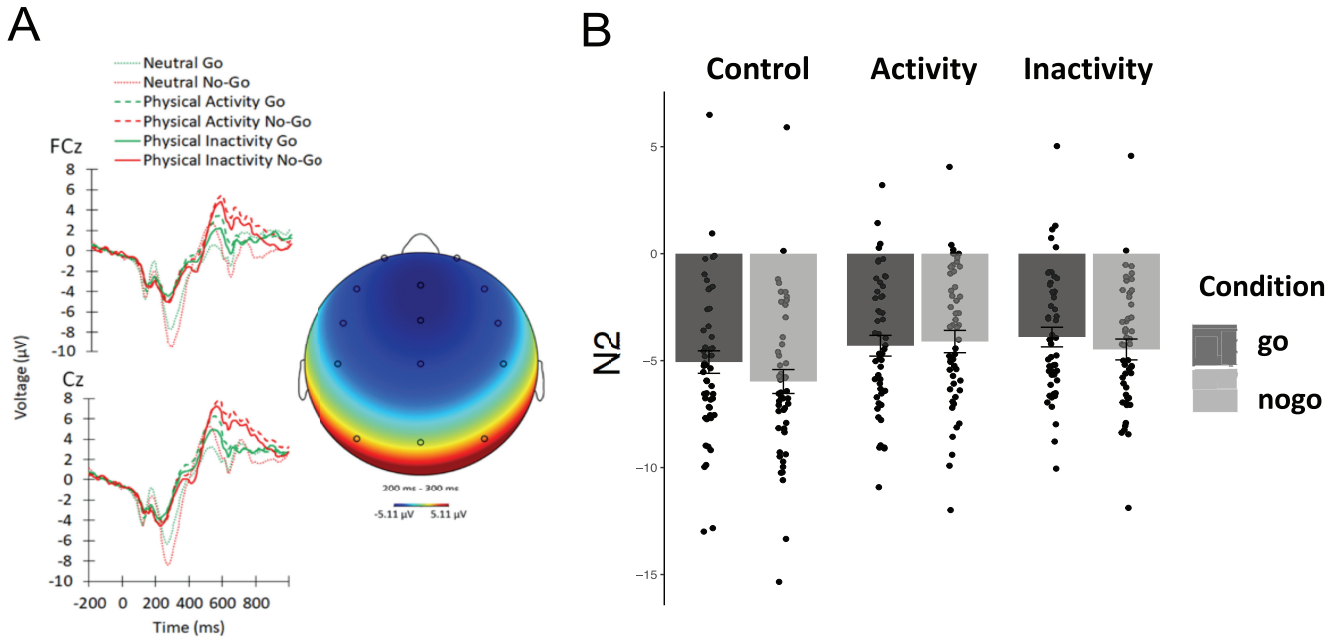
across type of trial and stimuli. MEM results revealed a two-way interaction between the type of trials and the type of stimuli, suggesting that the effect of the type of trials on N2 significantly varied depending on the type of stimuli (p for global effect = .001). Simple interaction tests further revealed that the effect of the type of trials on N2 significantly differed between stimuli depicting physical activity compared with physical inactivity (b = –.78 μV, 95% CI = –1.38 to –.18 μV, p = .011) or control (b = –1.11 μV, 95% CI= –1.71 to –.50 μV, p < .001). No differences were observed between stimuli depicting physical inactivity and control

Figure 2
Go/No-Go Behavioral Outcome



Note. Commission error. The odds ratio of a failure of inhibition in the no-go trials to stimuli depicting physical activity, control, and physical inactivity. Errors bars represent the 95% confidence interval around the mean. Dots represent the observations for each participant.

Figure 3
N2 Outcomes



Note. A. Grand average ERPs and topoplot. The grand average ERPs are presented as a function of the type of trials and the type of stimuli, and the topoplot is presented averaged across type of trials and stimuli. Grand average ERPs reveal an N2 component peaking between 200 and 300 ms. The topoplot demonstrates a stereotypical N2 frontocentral scalp distribution. B. N2 mean amplitudes. Data points representing mean amplitude for each participant as a function of the type of trial (i.e., go vs. no-go) and the type of stimuli (i.e., control vs. physical activity vs. physical inactivity). Errors bars represent the 95% confidence interval around the mean. Dots represent the observations for each participant. See the online article for the color version of this figure.

stimuli (b = .33 μV, 95% CI = –.27 to .93 μV, p = .285). Simple effects showed a more negative N2 amplitude for no-go trials compared with go trials for both control stimuli (b = –.91 μV, 95% CI = –1.42 to –.40 μV, $p < .001$) and stimuli depicting physical inactivity (b = –.58 μV, 95% CI = –1.08 to –.08 μV, p = .025). For stimuli depicting physical activity, results did not show any significant difference in N2 amplitude between no-go and go trials (b = .20 μV, 95% CI = –.31 to .70 μV, p = .445) (Table 3, Figure 3B). The variables under consideration explained 11.5% of the variance in N2. The interactive effects between the type of trials and the type stimuli on N2 were not moderated by the usual level of physical activity (ps > .330).

In sum, results revealed a typical no-go effect (i.e., more negative N2 amplitudes for no-go trials compared to go trials) for both control and physical inactivity stimuli, but no such effect was found for physical activity stimuli.

FMθ

Figure 4A shows grand average time-frequency plots as a function of type of trial and stimuli as well as FMθ scalp distribution averaged across type of trial and stimuli. Results revealed a two-way interaction between the type of trials and the type of stimuli, suggesting that the effect of the type of trials on FMθ significantly varied depending on the type of stimuli (p for global effect = .030). Simple interaction tests further revelated that the effect of the type of trials on FMθ was significantly less pronounced for physical activity (b = .70 μV^2, 95% CI = .09 to 1.31 μV^2, p = .026) and physical inactivity stimuli (b = –.74 μV^2, 95% CI = –1.35 to –.13 μV^2, p = .018) compared with control stimuli. No significant differences were observed between stimuli depicting physical activity and physical inactivity (b = –.04 μV^2, 95% CI = –.64 to .57 μV^2, p = .900). Simple test effects further showed a significant effect of the type of trials, regardless the type of stimuli: Greater FMθ was observed on the no-go trials compared to the go trials for physical inactivity stimuli (b = 2.32 μV^2, 95% CI = 1.64 to 3.00 μV^2, $p < .001$), physical activity stimuli (b = 2.36 μV^2, 95% CI = 1.68 to 3.04 μV^2, $p < .001$), and for control stimuli (b = 3.06 μV^2, 95% CI = 2.38 to 3.75 μV^2, $p < .001$). The variables under consideration explained 5.1% of the variance in FMθ (Table 4).

In addition, results showed that the interactions between the type of trial and the type of stimuli were moderated by the usual level of physical activity (although p for global effect = .091). Simple effect tests further revealed that usual level of physical activity significantly moderated the difference in the effect of the type of trials on FMθ between physical inactivity stimuli and control stimuli (b = –.70 μV^2, 95% CI = –1.35 to –.05 μV^2, p = .034) as well as between physical inactivity stimuli and physical activity stimuli (b = –.82 μV^2, 95% CI = –1.47 to –.17 μV^2, p = .014). The decomposition of these three-way interactions showed that the relationship between the typical no-go effect and usual physical activity was negative for physical inactivity stimuli but positive for physical activity and control stimuli. Specifically, for physical inactivity stimuli,

Table 3
Results of the Mixed Models Predicting N2 ERP

N2	Without MVPA (n = 50)		With MVPA* (n = 43)	
	b (CI)	p	b (CI)	p
Fixed effects				
Intercept	−4.30 (−5.25, −3.35)	<.001	−4.10 (−5.05, −3.13)	<.001
Type of trials (ref. go trials)				
No-go trials	.20 (−.31, .70)	.445	.24 (−.30, .78)	.387
Stimuli (ref. physical activity stimuli)				
Physical inactivity	.41 (−.18, .99)	.176	.40 (−.22, 1.01)	.207
Control	−.76 (−1.56, .03)	.063	−.76 (−1.64, .12)	.094
Type of Trials (ref. Go trials) × Stimuli (ref. physical activity stimuli)				
Physical Inactivity Stimuli × No-Go Trials	−.78 (−1.37, −.18)	.011	−.73 (−1.36, −.09)	.026
Control Stimuli × No-Go Trials	−1.11 (−1.70, −.50)	<.001	−1.16 (−1.81, −.52)	<.001
Usual level of physical activity				
Usual level of physical activity			−.69 (−1.61, .22)	.144
Usual Level of Physical Activity × Physical Inactivity Stimuli			−.11 (−.58, .35)	.637
Usual Level of Physical Activity × Control Stimuli			.03 (−.76, .83)	.933
Usual Level of Physical Activity × No-Go Trials			−.46 (−.08, 1.01)	.097
Usual Level of Physical Activity × Physical Inactivity Stimuli × No-Go Trials			−.32 (−.96, .32)	.330
Usual Level of Physical Activity × Control Stimuli × No-Go Trials			−.28 (−.93, .36)	.389
p-value for global effect	<.001			
Random effects				
Participants				
Intercept	9.920		8.788	
Stimuli physical inactivity	1.155		1.297	
Stimuli control	5.240		5.971	
Type of trials				
Corr. (Intercept, stimuli physical inactivity)	−.36		−.39	
Corr. (Intercept, stimuli control)	−.19		−.28	
Corr. (Stimuli physical inactivity; stimuli control)	.55		.63	
Corr. (Intercept, type of trials)	−.06		−.12	
Corr. (Stimuli control, type of trials)	0		−.02	
Corr. (Stimuli physical inactivity, type of trials)	−.19		−.19	
Stimuli				
Intercept	.864		.840	
Residual	89.53		88.05	
R^2	.116		.108	

Note. CI = confidence interval at 95%; MVPA = moderate-to-vigorous physical activity.
* With MVPA, the final sample size is N = 43, because 7 participants did not report their usual physical activity level.

results showed that the greater FMθ observed on the no-go trials compared to the go trials was less pronounced when the usual level of physical activity was higher. The region of significance of this no-go effect was no longer significant in highly active participants (+1.9 *SD*). By contrast, for physical activity stimuli, results showed that the greater FMθ observed on the no-go trials compared to the go trials was more pronounced when the usual level of physical activity was higher. However, the region of significance showed that the no-go effect was significant even in the least active individuals (see Supplemental material 2).

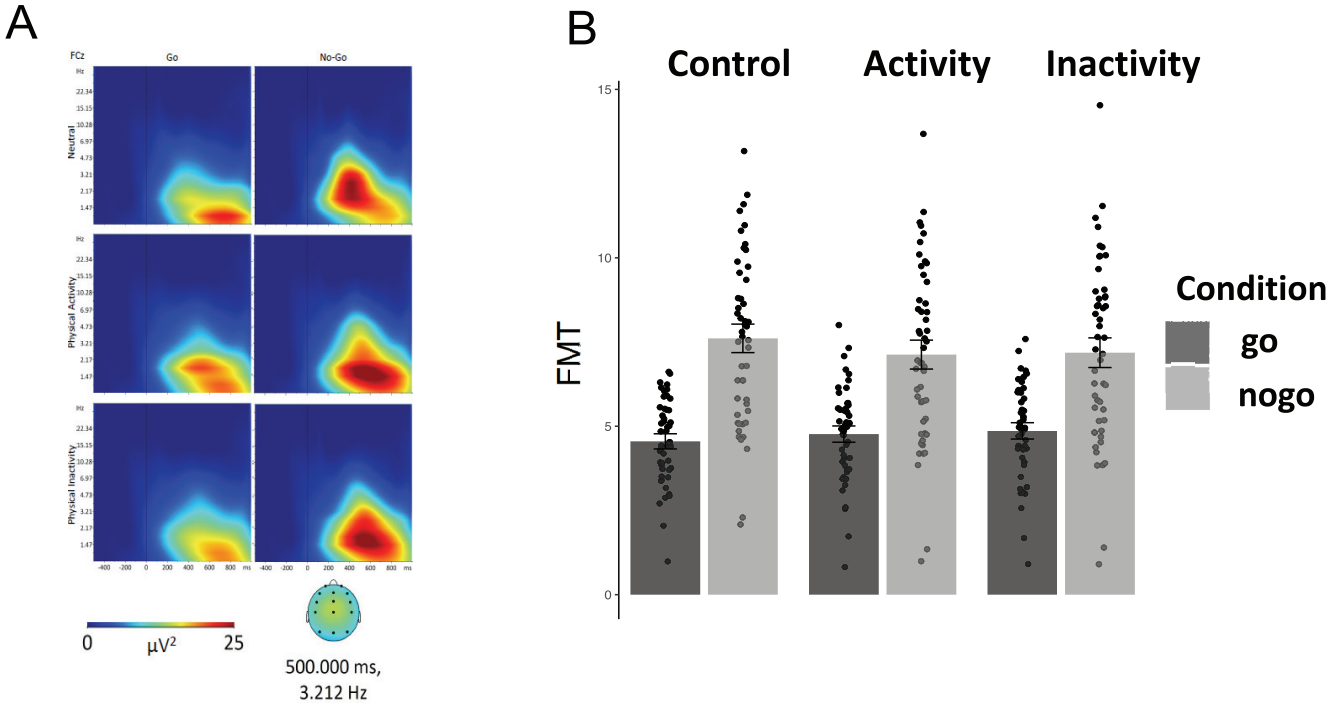
In sum, results revealed that the no-go effect (i.e., more positive FMθ for no-go trials compared to go trials) for physical inactivity stimuli decreased as the usual level of physical activity increased. On the contrary, the no-go effect for physical activity stimuli showed the reverse pattern—increased as the usual level of physical activity increased. However, it should be noted that the usual level of physical activity did not significantly moderate the no-go effect for a given type of stimuli. The significant three-way interaction was observed because, for physical inactivity stimuli, the direction of the relationship between the no-go effect and usual level of physical activity was opposite from that of the two other types of stimuli.

Discussion

Main Findings

The present study drew on the data from Cheval, Daou, et al.'s (2020) study and used EEG to elucidate the neural mechanisms underlying the higher failure to withhold responses to physical inactivity stimuli. We found evidence that participants exhibited larger N2 for inhibiting responses (vs. responding) to physical inactivity stimuli relative to physical activity stimuli. Of note, we observed a typical no-go effect found in previous studies for both physical inactivity and control stimuli (Folstein & Van Petten, 2008), while no significant effect on N2 was observed for physical activity stimuli. EEG results are consistent with behavioral results showing higher commission errors (i.e., failure to withhold the behavioral response) when participants inhibited their responses to physical inactivity stimuli, compared with physical activity stimuli. Hence, our study suggests that withholding responses to physical inactivity stimuli requires increased inhibitory control relative to withholding responses to physical activity stimuli (commission error and N2 results), findings that are in line with TEMPA

Figure 4
Frontal Midline Theta (FMθ) Outcomes



Note. A. Grand average time-frequency plots (FCz electrode). The grand average time-frequency plots are presented as a function of the type of trials and the type of stimuli, and the FMθ scalp distribution averaged across type of trial and stimuli is presented. Grand average time-frequency plots reveal low-frequency activity peaking just after 500 ms. The topoplot of this activity reveals a stereotypical frontocentral scalp distribution. B. FMθ power. Data points representing FMθ power for each participant as a function of the type of trial (i.e., go vs. no-go) and the type of stimuli (i.e., control vs. physical activity vs. physical inactivity). Errors bars represent the 95% confidence interval around the mean. Dots represent the observations for each participant. See the online article for the color version of this figure.

(Cheval & Boisgontier, 2021). Neither the N2 nor the commission error results were moderated by participants' usual level of physical activity.

Regarding the effects for control stimuli, results showed that inhibitory responses were associated with lower commission errors and a larger no-go effect for FMθ in comparison to physical activity and inactivity stimuli. For N2, control stimuli elicited a larger no-go effect than physical activity stimuli, and a similar no-go effect to physical inactivity stimuli. Taken together, these results suggest that participants are better at inhibiting control stimuli than physical activity and physical inactivity stimuli (i.e., fewer commission errors), but may require stronger inhibitory control (i.e., larger FMθ and N2 no-go effects), at least relative to physical activity stimuli, to do so. However, at least three features of the control condition preclude the validity of these conclusions.

First, the control stimuli were not truly neutral. The average valence for neutral images was 6.34 out of 9 (based on the International Affective Picture System). As such, although the valence (as well as arousal and dominance) of the images that included an animal matched the valence of the images that did not, these images were not, on average, neutral. Accordingly, we cannot assume that the level of inhibition required to avoid these stimuli reflects the one associated with neutral (i.e., nonvalenced) stimuli. Second, the control stimuli did not match the complexity of physical activity and inactivity stimuli. Specifically, the physical activity and inactivity stimuli featured the same person in either a physically active or inactive position with a blue background, whereas the control stimuli included multiple items and a more variable and complex background, which may therefore have required greater early visual processing. This difference in complexity likely affected the amplitude of the N1 ERP component (see negative deflection between 100 and 150 ms in ERPs depicted in Figure 3A), which is clearly larger for control stimuli than physical activity and inactivity stimuli. These N1 differences confound the interpretation of subsequent N2 differences between control stimuli and physical activity and/or inactivity stimuli (i.e., make it difficult to determine whether they are related to inhibitory control or visual processing). Finally, the different instructions of the control condition appear to have unexpectedly required dissimilar degrees of inhibitory control. In particular, we found a typical no-go effect of –2.05 μV for the control condition wherein participants were asked to avoid nonanimal images (i.e., –5.53 μV for responding to an image depicting an animal vs. –7.58 μV for avoiding an image without an animal), which is larger than the no-go effect for physical inactivity (–.58 μV) and physical activity (.20 μV) stimuli. For the control condition in which participants were asked to avoid animal images, we observed a smaller typical no-go effect of –.27 μV (i.e., –5.25 μV for responding to an image not depicting an animal vs. –5.52 μV for avoiding an image depicting an animal), a result that is descriptively between the no-go effect for physical inactivity and activity stimuli.

Table 4
Results of the Mixed Models Predicting Frontal Midline Theta (FMθ)

	Without MVPA (n = 50)		With MVPA* (n = 43)	
Frontal midline theta (FMθ)	b (CI)	p	b (CI)	p
Fixed effects				
Intercept	4.77 (4.29, 5.24)	<.001	4.82 (4.31, 5.32)	<.001
Type of trials (ref. Go trials)				
No-go trials	2.36 (1.68, 3.04)	<.001	2.12 (1.43, 2.83)	<.001
Stimuli (ref. physical activity stimuli)				
Physical inactivity	.10 (−0.31, .50)	.645	−.13 (−.56, .31)	.574
Control	−.22 (−.71, .28)	.396	−.27 (−.80, .25)	.310
Type of Trials (ref. Go trials) × Stimuli (ref. physical activity stimuli)				
Physical Inactivity Stimuli × No-Go Trials	−.04 (−.64, .57)	.900	−.41 (−.24, 1.05)	.218
Control Stimuli × Go Trials	.70 (0.09, 1.31)	.026	.71 (.05, 1.36)	.034
Usual level of physical activity				
Usual level of physical activity			−.15 (−.64, .35)	.563
Usual Level of Physical Activity × Physical Inactivity Stimuli			−.06 (−.47, .35)	.781
Usual Level of Physical Activity × Control Stimuli			.05 (−.46, .55)	.863
Usual Level of Physical Activity × No-Go Trials			.15 (−.55, .85)	.678
Usual Level of Physical Activity × Physical Inactivity Stimuli × No-Go Trials			−.70 (−1.35, −.05)	.034
Usual Level of Physical Activity × Physical Control Stimuli × No-Go Trials			.16 (−.54, .77)	.728
p-value for global effect	<.001		= .091	
Random effects				
Participants				
Intercept	2.214		2.172	
Stimuli physical inactivity	.721		.766	
Stimuli control	1.814		1.734	
Type of trials				
Corr. (Intercept, stimuli physical inactivity)	−.27		−.44	
Corr. (Intercept, stimuli control)	−.54		−.49	
Corr. (Stimuli physical inactivity; stimuli control)	.33		.45	
Corr. (Intercept, type of trials)	.24		.24	
Corr. (Stimuli control, type of trials)	.01		.02	
Corr. (Stimuli physical inactivity, type of trials)	.14		.11	
Stimuli				
Intercept	.072		.085	
Residual	86.68		85.27	
R^2	.051		.049	

Note. CI = confidence interval at 95%; MVPA = moderate-to-vigorous physical activity.
* With MVPA, the final sample size is n = 43, because 7 participants did not report their usual physical activity level.

Therefore, the directionality of the no-go effect in the physical activity and inactivity conditions relative to the control condition depends on the instructions of the control condition. For the aforementioned reasons (i.e., valence and visual complexity of the control stimuli, as well as dissimilar inhibitory control requirements for the different instructions of the control condition), we believe that the control condition does not stand as an accurate one. Future studies should rely on more comparable and neutral control stimuli.

In the remainder of the discussion, we couch our results in light of previous studies and then highlight the strengths and weaknesses of the current study. For the abovementioned reasons, we focus on the comparison between results observed for physical activity and inactivity stimuli. Indeed, due to the concerns related to the control condition, we believe the current data cannot accurately disentangle whether physical inactivity (activity) stimuli required higher (lower) inhibitory control relative to control stimuli.

Comparison With Other Studies

Results are consistent with a prior go/no-go study using EEG that revealed greater inhibitory control is demanded when avoiding attractive stimuli related to unhealthy eating behaviors (Carbine et al., 2017). However, whereas the prior study concerned energy consumption (e.g., low-calorie vs. high-calorie food), the present study focused on energy expenditure and showed results consistent with the assumption that cognitive resources are important for inhibiting responses to physical inactivity stimuli. Hence, our findings lend support to existing epidemiological and experimental studies (Cheval, Orsholits, et al., 2020; Cheval, Tipura, et al., 2018; Hall et al., 2008). For example, in Cheval, Tipura, et al.'s (2018) study, it was found that avoiding visual stimuli depicting sedentary behaviors was associated with larger N2 amplitudes. Furthermore, the current results align with recent perspectives (Buckley et al., 2014) and novel theories about physical inactivity and exercise (Brand & Cheval, 2019; Brand & Ekkekakis, 2018; Conroy & Berry, 2017). In particular, results are largely in line with the TEMPA, from which the present study's hypotheses were drawn (Cheval & Boisgontier, 2021). Indeed, the TEMPA proposes that humans have an automatic attraction toward effort minimization, meaning extra cognitive resources are required to avoid it.

We found significant two-way interactions between the type of trials and the type of stimuli, revealing that the effect of the type of trials (i.e., the no-go effect) significantly differed between physical activity stimuli and control or physical inactivity stimuli, while no

significant differences were observed between control and physical inactivity stimuli. Simple tests further revealed that the typical no-go effect observed in previous studies (i.e., higher N2 in no-go relative to go trials; Folstein & Van Petten, 2008) was observed for both control and physical inactivity stimuli, but not for physical activity stimuli. In other words, these results suggest that inhibiting responses to physical activity stimuli does not require as much inhibitory control as inhibiting responses to control or physical inactivity stimuli. These results contrasting physical activity and physical inactivity stimuli are consistent with previous literature that has suggested that people are naturally inclined to conserve energy and avoid unnecessary physical exertion (Brehm & Self, 1989; Gendolla et al., 2012; Silvestrini & Gendolla, 2013).

Further analyses on time-frequency data revealed that FMθ was higher for avoiding (vs. approaching) both physical inactivity and physical activity stimuli, and that participants' usual level of physical activity moderated these effects—greater FMθ for avoiding (vs. approaching) physical inactivity stimuli was stronger when usual level of physical activity was lower, while the FMθ effects for avoiding (vs. approaching) physical activity stimuli was stronger when usual level of physical activity was higher. This pattern of moderation was expected as we hypothesized that avoiding physical inactivity stimuli should require less inhibitory control in participants who manage to be physically active. However, this pattern should be interpreted in the light of our sample features—that is, a highly active sample. Likewise, in such physically active participants, additional inhibitory control could be required to avoid physical activity stimuli, because these stimuli may have acquired, across time, a certain attractive or rewarding value (Cheval, Radel, et al., 2018; Crombie et al., 2018; Raichlen et al., 2012; Raichlen et al., 2013). In sum, these findings may suggest that highly active individuals need less inhibitory control to counteract the automatic attraction to effort minimization, but more inhibitory control to withhold responses to physical activity opportunities. Of note, this higher inhibitory control to withhold responses to physical activity stimuli has been already observed in participants with anorexia nervosa, a disorder characterized by physical hyperactivity (Giel et al., 2013).

Strengths and Weaknesses

The present study has a few limitations. First, the images used in the task showed a model in exercise clothing in an exercise context (e.g., on an exercise mat). This could have increased stimulus conflict when the model was physically inactive, which could have increased the N2 and FMθ to these stimuli (Cavanagh & Frank, 2014). Future studies should avoid a potential confound with stimulus conflict, for example by using an avatar in an empty setting. Likewise, the control stimuli used in the current study were not truly neutral. Future research needs to rely on truly neutral stimuli to accurately investigate the directionality of the effects. Second, usual level of physical activity was indexed via self-report, which is prone to self-recall and desirability biases (Ward et al., 2005), thus limiting the ability to evaluate how participants' usual physical activity moderates the EEG effects observed. Finally, the present study involved individuals who were young and reported being highly physically active. These features limit the possibility to generalize the current results to other populations, such as older and/or less active individuals.

Conclusion

In conclusion, our results point out the neural mechanisms likely to underlie individuals' failure to withhold responses to physical inactivity stimuli, by showing that inhibiting such stimuli requires higher inhibitory control compared with inhibiting responses to physical activity stimuli. These results may indicate that physical inactivity opportunities are automatically attractive and thereby difficult to avoid, as suggested by the theory of effort minimization in physical activity (TEMPA; Cheval & Boisgontier, 2021) and other theoretical perspectives (Brehm & Self, 1989; Gendolla et al., 2012). By showing that the neural activity assumed to underlie the inhibition of responses significantly differed between physical activity and inactivity stimuli, our results shed light on the neuropsychological determinants of physical activity behaviors.

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