Cognitively engaging exercise predicts executive functioning on laboratory tasks

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ABSTRACT

The cognitive engagement hypothesis claims that regular exercise must be cognitively engaging in order to benefit executive functioning. However, the available evidence for this hypothesis is circumstantial. Here we look for correlational evidence for the hypothesis in two studies. In Study 1, 145 young adults first reported the extent to which their primary exercise and non-exercise leisure activities were cognitively engaging. They then completed two well-known laboratory tasks measuring executive function: a flanker task to index inhibitory control and a backward digit span task to assess working memory. Structural equation modeling revealed that when participants reported that their exercise relied on inhibitory cognitive control, they performed better on the flanker task, and, when their exercise demanded cognitive flexibility, they performed better on a backward digit task. These relationships did not hold for their primary reported leisure activity. Study 2 confirmed this finding with an independent sample of 227 undergraduates and two different executive function tasks: a stop-signal task to index inhibitory control and a trail making B task to assess cognitive flexibility. When participants reported that their regular exercise relied on inhibitory control they had faster stop-signal reaction times and made fewer trail making errors, and, when their exercise relied on cognitive flexibility, they had slower stop-signal reaction times and longer trail making B completion times. These relationships were again not found for participants' leisure activities. These findings support the central hypothesis that exercise is associated with cognitive performance on laboratory tasks, provided the exercise is itself cognitively demanding.

Keywords

exercise, cognition, executive function, cognitive engagement

Citation:

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Introduction

There is strong evidence that physical exercise is positively associated with cognitive functioning. Some of the strongest evidence comes from randomized control trials involving fitness training programs for older adults (see meta-analysis by Colcombe & Kramer, 2003), and there is even evidence of benefits to preadolescent children engaging in a single bout of moderate aerobic exercise (see review by Chaddock et al., 2011). Reviews of the evidence for an exercise-cognition link across the lifespan tend to find the strongest and most consistent evidence in early development and in aging populations, though there are plenty of reports showing correlations in young adult populations at the peak of their athletic and cognitive abilities (Kozik & Enns, 2021; Ludyga et al., 2020; Pesce et al., 2023; Voss et al., 2011). These reports have led to a search for the neuro-physiological bases of the exercise-cognition link. Some of the top-contending evidence considers the influence of exercise on the volume of the dorsolateral prefrontal cortex (Weinstein et al., 2012), the temporal cortex (Yuan & Raz, 2014), and the hippocampus (Erickson et al., 2011). Other evidence considers the role of exercise in brain oxygenation (Kujach et al., 2018) and in increases in the concentration of brain-derived neurotrophic factors (BDNF) implicated in the formation of new neurons (Liu & Nusslock, 2018).

The exercise-brain relationship is also modulated by multiple behavioral factors. Intense exercise (e.g., sprinting) shows stronger correlations with executive functioning tasks than light exercise (e.g., walking) in studies involving acute bouts of exercise (Gejl et al., 2018). Longer acute bouts of exercise correlate more strongly with cognitive functioning than shorter bouts (Colcombe & Kramer, 2003). The cognitive benefits of long-term regular exercise are greater than those of acute exercising (Padilla et al., 2014). The type of exercise also matters (Soga et al., 2018), with exercise in dynamic environments (e.g., badminton) tending to elicit a stronger neurotrophic response than exercise in more static environments (e.g., treadmill running). In a systematic review of the benefits of dynamic over static exercise environments, Gu et al. (2019) concluded that the most consistent evidence favoring dynamic environments came from observational studies of children and older adults. Results of direct intervention studies were weaker (Hung et al., 2018) and some observational studies reported mixed findings (Becker et al., 2018).

Beyond these broad trends, some researchers speculate that a critical factor may be whether one's regular exercise is cognitively engaging. Tomporowski (1997), writing about exercise in older adults, speculated that there might be sufficient commonalities between physical and mental exercise to support common explanatory theories. Fabel & Kempermann (2008), writing about hippocampal neurogenesis in the aging rat brain, speculated that rather than isolated physical activity being the critical ingredient, it was physical activity combined with cognitive challenges that led to the best results. Best (2010), writing about children's executive function, proposed that cognitively engaging exercise might have stronger effects than non-engaging exercise. Diamond & Ling (2016), reviewing the evidence on exercise and cognition put it most bluntly, "boring exercise is particularly unlikely to yield cognitive benefits" (pp. 38-39).

Some of the challenges involved in testing the *cognitive engagement hypothesis* are the large individual differences in types of exercise, the variety of settings, and the diverse conditions under which exercise occurs. As a result, any particular exercise can be very cognitively engaging for some people, but less engaging for others. Likewise, a particular physical activity can be an exercise involving inhibitory control for some, but others may find that it challenges their cognitive flexibility. Here we take the direct approach of asking exercise adherents whether and how they find their primary exercise to be cognitively engaging. This measurement approach matches the theoretical construct, because whether an exercise is cognitively engaging is a question that only each individual can answer. As such, it takes into account that the same exercise may be more engaging for some than others. But its strongest feature is that it offers the test of a very specific prediction: if a primary exercise depends heavily on one aspect of cognitive function, then it should predict relatively better performance on a laboratory measure of that aspect.

There is general consensus that the planning of everyday activities, the pursuit of small and large life goals, and the solving of daily problems can be considered under the umbrella term of executive functioning, also referred to as frontal lobe functions (Miyake et al., 2000; Sachdev et al., 2014; Soga et al., 2018). Executive functions are therefore central to healthy mental function (American Psychiatric Association, 2013), along with five other dissociable domains of cognitive function, including complex attention, learning and memory, language, perceptual–motor function, and social cognition (Sachdev et al., 2014). A primary reason for us to focus on executive functions in the exercise-cognition domain is that in a recent exhaustive review of the literature on attention and athletics, we examined laboratory tasks measuring a diverse range of visual-cognitive tasks, including spatial orienting, spatial shifting of attention, the spatial distribution of attention, temporal sequencing of actions, and the control of attention. The results of the review indicated that the vast majority of studies pointed to the control of action and attention as lying at the nexus of athletics-cognition correlation (Kozik & Enns, 2021).

The umbrella term of *executive function* is often further subdivided into separate functions of inhibitory control, cognitive flexibility, and working memory (Sachdev et al., 2014). Inhibitory control allows one to ignore distracting sights or sounds and to stop oneself from acting on impulse when receiving unexpected information (Pardini et al., 2004; Verbruggen et al., 2013). Cognitive flexibility refers to how efficiently one can shift from one mode of thinking or channel of information to another mode or channel. Working memory refers to how effectively one can store and manipulate multiple sources of information over several seconds (Diamond, 2013). Table 1 documents the close relationship between each questionnaire item we developed and the background research that inspired it.

There are theoretical reasons to suspect that the benefits of exercise might be specific to the kinds of cognitive demands made by a given exercise type. A primary reason favoring the cognitive engagement hypothesis comes from the literature on the transfer of training. Several highly cited reviews of how training in one context generalizes to success in another context all agree that there is a sharp gradient of generalization (Katz et al., 2018; Moreau, 2022; Simons et al., 2016). Learning transfers most readily when the contexts of study and test are most similar (near transfer), with successful transfer falling off as contexts become more different (far transfer). Applied to the question of exercise-related benefits for cognition, this conclusion implies that exercise-training benefits will correlate with the similarity between the cognitive requirements of an exercise and a test of a specific cognitive function. For exactly this reason, and after reviewing numerous theoretical and methodological pitfalls of the studies in this area, Furley et al. (2023) cautions against selling sports and exercise as domain-general training for executive functioning. A recent study by Ehmann et al. (2022) further emphasizes the narrow scope by which exercise and cognition may be linked. These authors tested elite and sub-elite soccer players, from ages 12 to 23 years, on a full-surround, multiple object-tracking task. They found differences favoring elite over sub-elite players only in the oldest (most experienced) age groups, which they attributed to the similarity of the tracking task to the conditions of real-life soccer.

The most general version of the cognitive engagement hypothesis we test in this study is that exercise perceived to rely on executive functioning will predict better performance on tasks designed to assess inhibitory control, cognitive flexibility, and working memory. But because of our own and other's skepticism concerning far transfer effects (see Fransen, 2022; Furley et al., 2023), we think there is a greater chance of finding support for near over far transfer effects. Namely, if a primary exercise depends heavily on inhibitory control, it should predict relatively better performance on a laboratory measure of inhibitory control (e.g., flanker task) than on a measure of working memory (e.g., backward span). And in a similar vein, if an exercise depends heavily on working memory, then it should predict relatively better performance on a laboratory measure of working memory (e.g., backward span) than on a measure of inhibitory control (e.g., flanker task). Support for this hypothesis would be consistent with greater success for near versus far transfer of learning effects. Finally, in addition to these two hypotheses assessing the sensitivity of the cognitive engagement hypothesis, there is a specificity hypothesis that limits the associations to exercise-specific activities. This means that if similar correlations were found for both the exercise and the non-exercise leisure activities of an individual, we would have to conclude that exercise is not unique. Instead, people with specific strengths among the executive function dimensions might simply be seeking out activities in their daily lives that capitalize on those strengths.

To summarize all these considerations, the hypotheses tested in the correlational studies that follow can be arranged on a continuum from specific to most general. The most specific hypothesis is that participants' self-reports of the executive function requirements of their regular exercise will correlate most strongly with laboratory tasks that are tied to the particular type of executive function they identify (i.e., inhibitory control, cognitive flexibility, working memory). A second and more general hypothesis is that self-reports will correlate more with all laboratory task performance, with little specificity between the type of executive function and the laboratory tasks. The third and most general hypothesis is that participants' self-reports will not only correlate with the executive function demands of their regular exercise but with the executive function demands of their non-exercise leisure activities as well. Support for this last hypothesis would be strong evidence against the cognitive engagement hypothesis, since it could be interpreted as simply reflecting each participant's more general cognitive abilities, rather than any more specific link between exercise and cognition.

Study 1

The first study was designed to test the hypothesis that cognitively engaging regular exercise predicts executive functioning on a laboratory test. Volunteer participants who were students at a large state-funded university filled out a survey about their exercise and leisure activities and then completed two cognitive tasks in exchange for partial course credit in psychology methodology courses. In the survey, participants self-reported their primary regular exercise (i.e., the exercise they had done most frequently in the past six weeks) and answered 30 questions about executive function use during exercise. The same was done for a non-exercise leisure activity. The laboratory tasks were a flanker task to measure inhibitory control and a backward span task to measure working memory. These two tasks were chosen because of their frequent use within the executive function literature, as well as because of their common use within the exercise and sport literatures (Chiu et al., 2017; Kamijo et al., 2009; Wylie et al., 2018). Both of these tasks have shown very robust reliability and validity when tested at a group level, though their reliability is considerably less, though still significant, at the individual participant level (Paap & Sawi, 2016; Waters & Caplan, 2003).

Method

Transparency and openness

This study was not preregistered. We report a priori power analyses for the sample size. All of the data files and the statistical code used to analyze the data in this study are posted here: https://osf.io/cse4t/?view_only=2125834d3a894994aedef0866ac7c2ee

Estimated sample size

To determine sample size we conducted a power analysis based on an anticipated measurement model. This model consisted of three latent factors (inhibitory control, cognitive flexibility, and working memory), with each factor allowed to freely correlate, and each indicated by 10 survey items. Following the procedures outlined in MacCallum et al. (1996), a sample size of 50 participants resulted in an estimated power of .86, given α = .05, ϵ_o = .07, ϵ_a = .10 and *df* = 402.

Because the survey questions were not previously validated, we anticipated the possibility that the data might not support this hypothesized structure, and so increased our target sample size to allow for modifications in the form of further exploratory analyses, model non-convergence, potential Heywood cases, and other concerns common to newly tested constructs deviating from an ideal solution. It was also difficult to anticipate a priori what proportion of the recruited participants would report regular exercise. For all these reasons, our target sample size was four times the size indicated by the power analysis, *N* = 200 (Boomsma, 1985; Holbert & Stephenson, 2002).

Participants

Participants were recruited through the University of British Columbia human study participant pool, following review and approval of the research plan by the University of British Columbia Behavioral Research Ethics Board (H18-03515). A total of 196 participants completed the one hour study and were provided 1% course credit. Following data filtering steps, the sample size included 145 participants who reported regularly engaging in physical exercise, 178 who reported having a leisure activity, and 143 who reported both activities.

Participants who reported exercising regularly were on average 20.43 years old (*SD* = 2.02), the majority were women (73.10%) and most identified as East Asian (45.52%), followed by European/Caucasian (23.45%), Indian-South (18.62%), Other (6.90%), African (2.76%), Middle Eastern (2.07%) and Latin American (0.69%). Figure 1A shows the frequency with which various types of exercise were reported, with exercises considered to be static versus dynamic indicated with shading. Static-dynamic categorization was based on common guidelines and past precedent (Chiu et al., 2017; Corrado et al., 2014). The most frequently reported exercises were running and weight training, followed by gym. Participants reported an average exercise history of seven months, with an average exercise duration of 60 to 90 minutes per week, and an average exercise intensity of moderate.

Participants who reported a primary leisure activity had very similar characteristics because most of them also reported exercising. Figure 1B shows the frequency with which various leisure activities were reported, with activities considered to be passive versus active indicated with shading. The most frequently reported leisure activity was viewing television, followed by gaming, and reading. Participants reported an average leisure history of nine months, with an average weekly duration of 90 to 120 minutes and an average leisure intensity of low.

Items to measure executive function in exercise

Table 1 shows the 30 items that were developed for this study to measure subjective perception of executive function use during exercise. They were developed after careful consideration of the central themes expressed in each of the references shown beside item. Items were preceded by, “when completing my primary

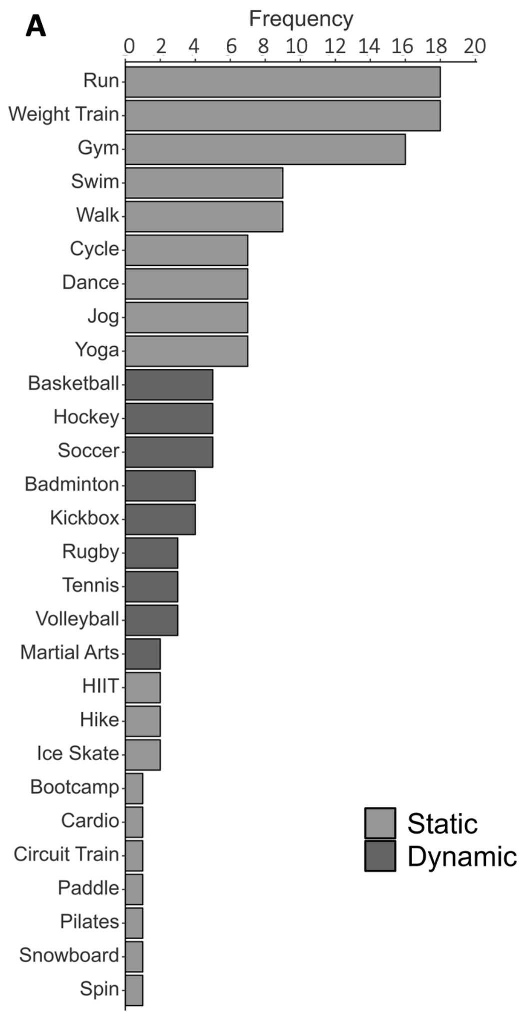

Figure 1 Self-reported exercise

(A) The relative frequency of reported primary exercise and (B) leisure activities in study 1. Type of exercise (dynamic or static) and leisure (active or passive) is shown in grayscale. See text for description of how the type was determined.

exercise, I…". Three sets of 10 questions were designed to measure inhibitory control, cognitive flexibility, and working memory. The second column in Table 1 shows the primary references and inspiration for the concept captured in the items. Half of all questions were positively worded and half were negatively worded, with negatively worded items being reverse scored in all analyses.

Table 1
Cognitive engagement items

Item	Reference for concept
When completing my primary exercise, I...	
Inhibitory control	
I1. slow down to avoid making mistakes	Pardini et al. (2004); Verbruggen et al. (2013)
I2. care most about speed and performing quickly (R)	Pardini et al. (2004); Verbruggen et al. (2013)
I3. filter and ignore distracting information	Diamond (2013)
I4. decide what to do through impulse alone (R)	Graziano et al. (2010); Tan & Holub (2011)
I5. practice self-control and discipline	Jacobson & Matthaeus (2014); Katzir et al. (2010)
I6. follow every action to completion (R)	Chu et al. (2015) ; Velzen et al. (2014)
I7. pause and double check what I am doing	Huster et al. (2020)
I8. start and complete actions without thinking (R)	Diamond (2013); Pardini et al. (2004); Verbruggen et al. (2013)
I9. anticipate making fast or sudden adjustments	Graziano et al. (2010); Tan & Holub (2011)
I10. act without self-restraint (R)	Pardini et al. (2004)
Cognitive flexibility	
C1. adapt and change how things are done	Kesler et al. (2011); Buttelmann & Karbach (2017)
C2. have a plan that I stringently follow (R)	Diamond (2013); Zelazo (2015)
C3. try to identify new techniques or strategies	Kesler et al. (2011); Buttelmann & Karbach (2017)
C4. follow the same routine (R)	Diamond (2013); Zelazo (2015)
C5. practice creativity	Kesler et al. (2011); Buttelmann & Karbach (2017)
C6. hold the same mindset from start to finish (R)	Diamond (2013); Zelazo (2015)
C7. encounter and solve new problems	Kesler et al. (2011); Buttelmann & Karbach (2017)
C8. have little-to-no flexibility to modify what I do (R)	Diamond (2013); Zelazo (2015)
C9. rely on a diverse skillset	Kesler et al. (2011); Buttelmann & Karbach (2017)
C10. think the same thoughts over and over (R)	Diamond (2013); Zelazo (2015)
Working memory	
W1. pay attention to many things at the same time	Bühner et al. (2006); Colom et al. (2010); Conway et al. (2007)
W2. understand everything that is happening even when absent-minded (R)	Ecker et al. (2014); Goldman-Rakic (1992); Miyake et al. (2000)
W3. make predictions about what will happen next	Baird et al. (2011)
W4. avoid time-keeping (R)	Ecker et al. (2014); Goldman-Rakic (1992); Miyake et al. (2000)
W5. connect and combine different ideas	Bühner et al. (2006); Colom et al. (2010); Conway et al. (2007)
W6. do not care about the order in which things happen (R)	Ecker et al. (2014); Goldman-Rakic (1992); Miyake et al. (2000)
W7. multitask	Bühner et al. (2006); Colom et al. (2010); Conway et al. (2007)
W8. disengage from what is happening around me (R)	Goldman-Rakic (1992); Miyake et al. (2000)
W9. monitor what is happening on a second-to-second basis	Ecker et al. (2014)
W10. focus all my attention entirely on one thing before moving onto the next (R)	Ecker et al. (2014); Goldman-Rakic (1992)

The 30 items used to assess the role of executive function in a participant's primary exercise. (R) denotes a reverse worded item. Each dimension (I = inhibitory control, C = cognitive flexibility, W = working memory) was represented by 10 items, based on the literature on executive functioning. Full citations for each study shown in the table are given in the reference section.

Procedure

Participants were given a consent form to read and sign upon arriving. Participants were seated in a small testing room and were told they would be completing a series of questionnaires, before being tested on two cognitive tasks. The first question participants answered was “Do you complete or take part in any form of exercise?”, with the option of answering “Yes” or “No”. If participants answered “Yes”, they completed a series of exercise and leisure questions, with the order of the question set (exercise or leisure) randomly determined. If participants answered “No” to the exercise question, they only answered a series of leisure questions.

Self-report measures

Following Chekroud et al. (2018), participants were asked: “People engage in many forms of exercise, including jogging, swimming, cycling, weight training, soccer, basketball, volleyball, rock-climbing, golf, yoga and various martial arts. Although there are many types of exercise, try to think of the one that you consider most central and primary for you. In the box below, type the name of your primary exercise. Only type the name of one exercise. If more than one exercise comes to mind, type the one you have done the most frequently in the past six weeks.” After identifying their primary exercise participants answered 30 Likert-scale questions intended to measure executive function use. Each question was answered by selecting a value ranging from 1 through 5, representing the terms 1 = *Never*, 2 = *Rarely*, 3 = *Sometimes*, 4 = *Often* and 5 = *Always*. We also categorized the exercise participants reported as static or dynamic based on past practice (Chiu et al., 2017; Corrado et al., 2014). Examples of static exercise included running and weight training, and examples of dynamic exercise included basketball and tennis, as shown in Figure 1.

Following these 30 questions, a set of qualifier questions measured exercise history, duration, and intensity (Colcombe & Kramer, 2003; Soga et al., 2018). History was measured by asking participants when they first began their primary exercise, with response options being *less than 1 month*, *1 to 3 months*, *4 to 6 months*, *7 to 9 months*, and *more than 9 months*. More than 80% of participants reported exercising regularly for more than 4 months and none of them reported exercising for less than one month. These data are shown in Table 2 of the appendix. Duration was measured by asking participants over the past 6 weeks how much time in a typical week was spent actively engaging in their primary exercise, with response options being *less than 30 minutes*, *30 to 60 minutes*, *60 to 90 minutes*, *90 to 120 minutes*, and *120 minutes or more*. Intensity was measured asking participants to rate the intensity of their primary exercise with response options being *none*, *low*, *moderate*, and *high*.

If participants reported not exercising, or were randomly assigned to complete leisure questions first, they saw the prompt: “People engage in many different leisure activities that are not related to exercise. These include drawing, writing, painting, reading, cooking, traveling, puzzle solving, carpentry, photography, theatre, politics, playing instruments, listening to music, and many others. Although there are many types of leisure activity try to think of the one that you consider most central and primary for you. In the box below, type the name of your primary (non-exercise related) leisure activity. Only type the name of one leisure activity. If more than one leisure activity comes to mind, type the one you have done the most frequently in the past six weeks.” Participants then answered 30 questions measuring executive function use during leisure activity, as well as questions meant to measure leisure history, duration and intensity. These leisure questions mirrored the exercise set of questions. Leisure activities were categorized, following Dardis et al. (1994), as either requiring active involvement in an activity (e.g., cooking) or as merely requiring passive participation (e.g., watching television).

Laboratory tasks

Executive function testing began after completing all questions. These tasks were designed so that they could be completed within the one hour session that is typical of studies for this cohort from the University participant pool. Each participant completed a flanker task and a backward span task, with the order determined randomly by the computer. These tasks were programmed using the Matrix Laboratory (MatLab), along with the *Psychophysics Toolbox* (Brainard, 1997; Kleiner, et al., 2007). The flanker task measures a form of inhibitory control that is sometimes referred to as interference control and was similar to many others reported in the attention and sport literature (e.g., Wylie et al., 2018). On each trial, participants reported the direction of a central arrow on the computer screen by pressing one of two keys as quickly and accurately as possible ("Z" for left pointing arrows and "/" for right pointing arrows). They were also told to ignore any other arrows on the screen, which could include flanking arrows that were either congruent with the central arrow (e.g., > > > > >) or incongruent (e.g., < < > < <).

Participants completed 10 practice trials with visual feedback before completing 200 test trials. Each trial began with a blank screen for 200 ms, followed by a small fixation cross for 500 ms, another blank screen for 200 ms, and then the target display of a central arrow flanked by distractor arrows. Congruent and incongruent trials were randomly determined, with the constraint that there were 100 of each. Flanker task reaction times were screened to exclude values less than 300 ms or greater than 1,500 ms, in order to avoid including responses based on anticipation and attention lapses, respectively (Chen et al., 2018).

The inhibitory measure from the flanker task is a difference score between congruent and incongruent trials. Specifically, accuracy for congruent trials was subtracted by accuracy for incongruent trials, and reaction time for incongruent trials was subtracted by reaction time for congruent trials. For both these metrics, larger values meant poorer inhibitory control. Figure 2A and Figure 2B summarize flanker task performance. Note that less than 5% of participants had small negative values on these measures, meaning that they were slightly faster or more accurate on the incongruent trials. None of these differences were significantly less than zero and so theoretically, we treated these participants as experiencing effectively no interference, although practically we kept their negative values in the analyses. The group results showed the expected flanker effect, where incongruent trials are completed significantly more slowly and less accurately than congruent trials.

The backward span task was modelled after Bourrier et al. (2018). On each trial, participants were shown a series of 3-9 digits presented one at a time at the center of a computer screen. Each digit appeared for 1 second. At the end of each series, a dialog box appeared just below the center and participants were asked to type the digits they had seen in reverse order. Participants were given two practice trials involving 3-digit sequences and accuracy feedback (i.e., the words *correct* or *incorrect* appeared at the center of the screen). For example, if the sequence included the digits 5-1-7, the correct answer was 7-1-5. During the first two test trials, the sequences were 3 digits in length, followed by two test trials of 4-digit sequences, and so on, until two 9-digit sequences had been presented.

Working memory capacity was scored by assigning each correctly reported digit a score of 1. Figure 2C summarizes backward span accuracy for all participants. These data depict the expected trend of near perfect accuracy for 3- and 4-digit sequences, but with asymptotic accuracy between 4 and 5 digits for sequences of lengths 5-9. Each participant received a capacity score based on the average number of correctly reported digits across all sequence lengths (Cowan, 2010).

Data analytic approach

Participants were excluded from the exercise or leisure analysis if they engaged in the reported activity for less than 1 month. Participants were also excluded for near-chance level accuracy on the backward span and flanker task (14% and 51% cut-offs), as well as if a participant listed an identical activity for both exercise and leisure (e.g., volleyball).

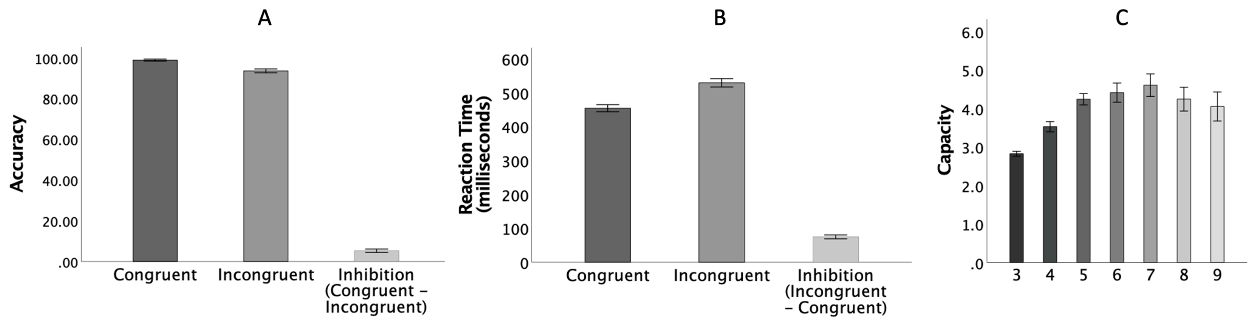

Figure 2 Executive function performance overall

(A) Mean accuracy on the flanker task for congruent and incongruent trials, with the mean difference shown in the third bar. (B). Mean response time on the flanker task for congruent and incongruent trials, with the mean difference shown in the third bar. (C) Mean number of digits correctly reported on the backward span task as a function of the number of digits shown. Error bars in A-C are +/- 1 standard error of the mean.

The first CFA included all 30 items measuring executive function use during exercise, with 10 items devoted to inhibitory control, cognitive flexibility and working memory. Descriptive statistics for these 30 items are in Table 3 of the appendix. CFA models were evaluated using a Chi-square test, but because this test tends to be sensitive to minor model misspecification (MacCallum et al., 1996; Steiger, 2007), we also examined alternative fit indices, including the root mean square error of approximation (RMSEA), the comparative fit index (CFI), and the standardized root mean square residual (SRMR). A well-fitting CFA model was defined as one that either had a non-significant Chi-square, or, if this standard could not be met, one that collectively had a CFI > .95, an SRMR < .08. and a RMSEA < .06 (Hu & Bentler, 1999).

Once a model that met these criteria was identified, it was used to predict performance on laboratory measures of executive functioning, along with exercise qualifiers (history, duration, intensity, and type). All structural equation models (SEM) and graphics were built using the statistical language *R* and the *lavaan* package (Rosseel, 2012). Model-based estimates of the significant parameters identified by the SEM were derived for each participant using the *lavPredictY* package in *R*, following the procedures in de Rooij et al. (2023). These parameters were compared for participants scoring either low or high (using a median split) on a self-reported dimension of executive function use in their regular exercise. These estimates are, of course, on the conservative side, since they force all the data into two binary categories (low, high). Nonetheless, they are useful in offering a practical comparison of the magnitude of the effects across the self-report variables that are identified by the SEM models.

Results

Exercise confirmatory factor analysis

An initial assessment of the internal consistency of the 30 measurement items yielded Cronbach's $\alpha = .60$. Values this high are considered quite good in the early stages of questionnaire development (Nunnally & Bernstein, 1994). We next use CFA to enforce the hypothesized allocation of items to the factors (Brown, 2015). The first CFA included 10 measurement items each for inhibitory control, cognitive flexibility, and working memory, as shown for item-to-factor loadings in Table 4 of the supplementary material. This model fit poorly, χ^2 (402) = 978.80, p < .001, RMSEA = .10, 90% CI [.09, .11], CFI = .50, SRMR = .12. Examining the model in greater detail, positively worded items tended to load positively and significantly (p < .05) on the hypothesized dimension, in support of the initial model. However, negatively worded items sometimes loaded negatively, as expected (7 of the items), sometimes non-significantly (6 items), sometimes even positively (2 items) suggesting that additional dimensions were being tapped. To remain within the hypothesized theoretical model, we performed additional explorations using CFA to keep enforcing the dimensions crucial for testing the specific hypotheses of the study.

In a follow-up CFA we dropped reverse worded items (DiStefano & Motl, 2006; Woods, 2006), but this model still fit poorly, χ^2 (87) = 218.06, p < .001, RMSEA = .10, 90% CI [.09, .12], SRMR = .11. the correlation between cognitive flexibility and working memory also held an impossibly high value of 1.02. We therefore combined these strongly correlated factors in a single latent construct. In what follows, we refer to this dimension as cognitive flexibility, both because items from that dimension were in the majority, and because the two working memory items that loaded on this factor (W3, W5) seemed to relate to flexible thinking more than on the control of working memory operations.

In an effort to find a better fitting model the remaining item pool was reduced to a smaller subset. Guidelines used in exploratory factor analysis suggest reviewing items with loadings falling below .30 (Pituch & Stevens, 2015) sometimes even below .50 (Briggs & MacCallum, 2003). Related advice included exclusion of cross-loadings, and not allowing fewer than 3 items per factor. We adopted an iterative process of removing the lowest factor loading below .50, and then re-examining the resulting model fit. If model fit was still below our set cut-offs, this process was repeated. A total of five additional items were removed, resulting in a model that fit our measurement criteria, (χ^2 = 44.83, p = .101, CFI = .97, SRMR = .06, RMSEA = .05, 90% CI [.00, .08]. Notably this model achieved a non-significant Chi-square test. This two-factor model had 10 items with three measuring inhibitory control and seven measuring cognitive flexibility, Table 5 in the appendix lists these remaining items with respective factor loadings. The 10 items had high internal consistency, Cronbach's α = .85, and the two factors were highly correlated with each other, r = .68. It is worth stating that although we used CFA to enforce the hypothesized allocation of items to factors, the approach was data-driven, as models were fit, evaluated, and adjusted, until a well-fitting measurement model was found.

Exercise structural equation modelling

Figure 3 shows the best fitting structural equation model (SEM) in Study 1. We used the two-factor model of executive function involvement in exercise described above to compute two factor scores for each participant indicating involvement of inhibition (Factor 1) and cognitive flexibility (Factor 2) in their exercise of choice. These two scores, combined with participant reported exercise qualifiers (history, duration, intensity, and type), were used in SEM to predict performance on laboratory measures of executive functioning. The main findings from this model were that involvement of inhibitory control in the exercise of choice predicted greater inhibitory control on the flanker task (i.e., a smaller accuracy difference between congruent and incongruent trials), β = -.33, B = -3.30, 95% CI [-6.46, -.13], p = .041[1], and exercise reported as relying on cognitive flexibility predicted greater working memory capacity on the backward span, β = .29, B = .57, 95% CI [.02, 1.12], p = .043. Inhibitory control, as measured by the RTs in the flanker task was not correlated with either of the two factors, ps > .18. None of the qualifiers contributed significantly to the model. The overall model yielded a significant Chi-square, χ^2 (98) = 163.50, p < .001, with alternative fit indices of RMSEA = .07, 90% CI [.05, .09], CFI = .87, SRMR = .12.

1. All p values for regressions within this manuscript are based on unstandardized coefficients (B and not β; Cudeck, 1989; MacCallum & Austin, 2000)

As a caution against the possibility of violations in multivariate normality, we also applied the Satorra & Bentler (1994) correction to this SEM model. The pattern of significant parameter estimates remained largely the same. Involvement of inhibitory control in exercise still predicted smaller accuracy differences between congruent and incongruent trials on the flanker task, β = -.33, *B* = -3.30, 95% CI [-6.13, -.46], *p* = .023, and involvement of cognitive flexibility in exercise predicted greater working memory capacity on the backward span, β = .29, *B* = .57, 95% CI [.05, 1.09], *p* = .033. The one notable difference in the model following the correction was that involvement of cognitive flexibility in exercise now also predicted poorer inhibitory control (a larger accuracy difference between congruent and incongruent trials on the flanker task), β = .26, *B* = 2.69, 95% CI [.21, 5.16], *p* = .033.

To help put some concrete values to the effect sizes identified by the SEM model, we examined each significant correlation (between self-reported executive function use and the laboratory measures) by comparing model-estimated parameters for participants who scored either low or high on each dimension using a median split. For example, consider the link between inhibitory control and flanker task inhibition in Figure 4A. Note that smaller scores reflect relatively better inhibitory control. Participants rating their exercise high in inhibitory control had inhibition scores (incongruent – congruent accuracy) that were significantly smaller (*M* = 5.10%, *SE* = 0.137) than participants rating their exercise low in inhibitory control (*M* = 5.81%, *SE* = 0.136), $t(143) = 3.63$, $p < .001$, Cohen's *d* = .56. A similar analysis was conducted on the link between cognitive flexibility and backward span capacity in Figure 4D. Here higher scores reflect relatively better working memory capacity. Participants rating their exercise high in cognitive flexibility, based on a median split, had estimated capacity scores that were significantly higher (*M* = 3.98, *SE* = 0.025) than participants rating their exercise as low in cognitive flexibility (*M* = 3.89, *SE* = 0.023), $t(143) = 2.66$, $p = .009$, Cohen's *d* = 0.044.

Although none of the exercise qualifiers were significant in the SEM, we were encouraged by a reviewer to examine exercise history (low, high) and type (dynamic, static) in a similar way, in an effort to seek further evidence of the validity of the laboratory measures in reflecting the benefits of exercise participation. The data in Figure 4B showed that participants rating their exercise history as longer had estimated flanker inhibition accuracy that was significantly smaller (*M* = 5.14%, *SE* = 0.107) than participants rating their exercise history as shorter (*M* = 6.16%, *SE* = 0.160), $F(1, 141) = 28.26$, $p < .001$, $np^2 = 0.167$. When the history factor was combined with the median split on inhibitory control, each of the main effects were strongly significant ($p < .001$) and there was no interaction ($p > .86$). A similar analysis examined exercise history and cognitive flexibility on the backward span capacity scores (Figure 4E). Participants rating their exercise history as longer had capacity scores that were significantly larger (*M* = 4.10, *SE* = 0.026) than participants rating their exercise history as shorter (*M* = 3.86, *SE* = 0.0173), $F(1, 141) = 59.67$, $p < .001$, $np^2 = 0.297$. When this factor was combined with median split on cognitive flexibility, each of the main effects were significant ($p < .002$), and there was no interaction ($p > .145$).

An examination of exercise type (dynamic, static) and these same measures revealed only one small significant effect involving backward span capacity (Figure 4F). Participants whose regular exercise was static had slightly larger capacity scores (*M* = 3.98, *SD* = 0.019) than participants reporting dynamic exercise (*M* = 3.76, *SD* = 0.043), $F(1, 141) = 21.20$, $p < .001$, $np^2 = 0.131$. When this factor was combined with median split on cognitive flexibility, each of the main effects were strongly significant ($p < .001$) and there was no interaction ($p > .23$).

Leisure confirmatory factor analysis and structural equation model

As the goal of the leisure data was to provide a comparable analysis to the exercise data, the same 10-items

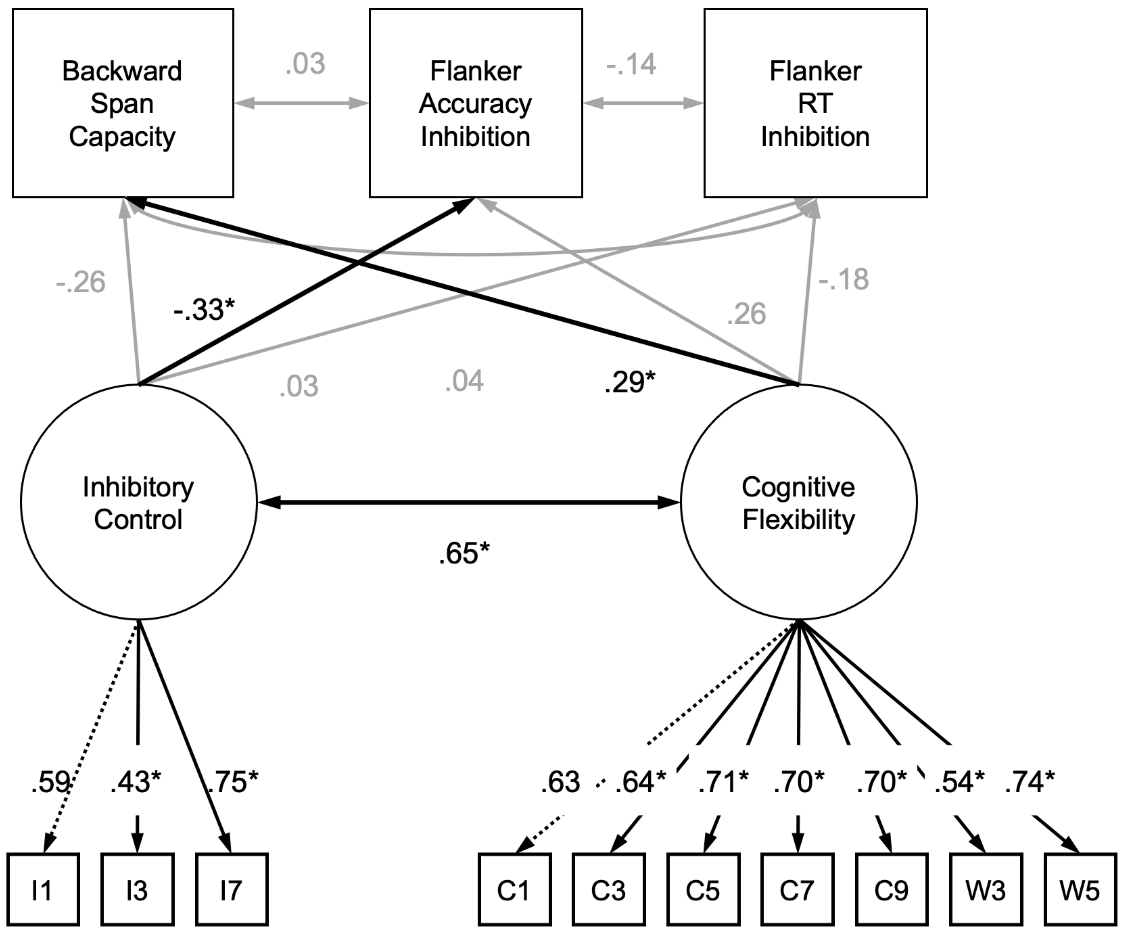

Figure 3 Linking exercise self-reports to performance

The best-fitting structural equation model in Study 1, showing the relations between laboratory task measures in the top row, the two latent constructs identified by confirmatory factor analysis in the middle row, and the 10 items that loaded significantly on the two latent constructs in the bottom row.

were used to create a leisure measurement model. The 10-item leisure measurement model had acceptable though slightly worse fit than the exercise measurement model, χ^2 (34) = 74.16, p < .001, RMSEA = .08, 90% CI [.06, .11], CFI = .95, SRMR = .05.

The 10-item leisure measurement model was combined with leisure qualifiers (history, duration, intensity, and type) to predict performance on laboratory tasks of executive functioning. No variables in this model predicted laboratory task performance. In particular, leisure reported to rely on inhibitory control did not predict an accuracy difference between congruent and incongruent flanker trials, β = .17, B = 1.12, 95% CI [-3.66, 5.91], p = .645, and leisure reported to rely on cognitive flexibility did not predict backward span performance, β = .77, B = 1.00, 95% CI [-.15, 2.14], p = .089. This model had a significant Chi-square, χ^2 (98) = 257.30, p < .001, with alternative fit indices of RMSEA = .10, 90% CI [.08, .11], CFI = .82, SRMR = .13[2].

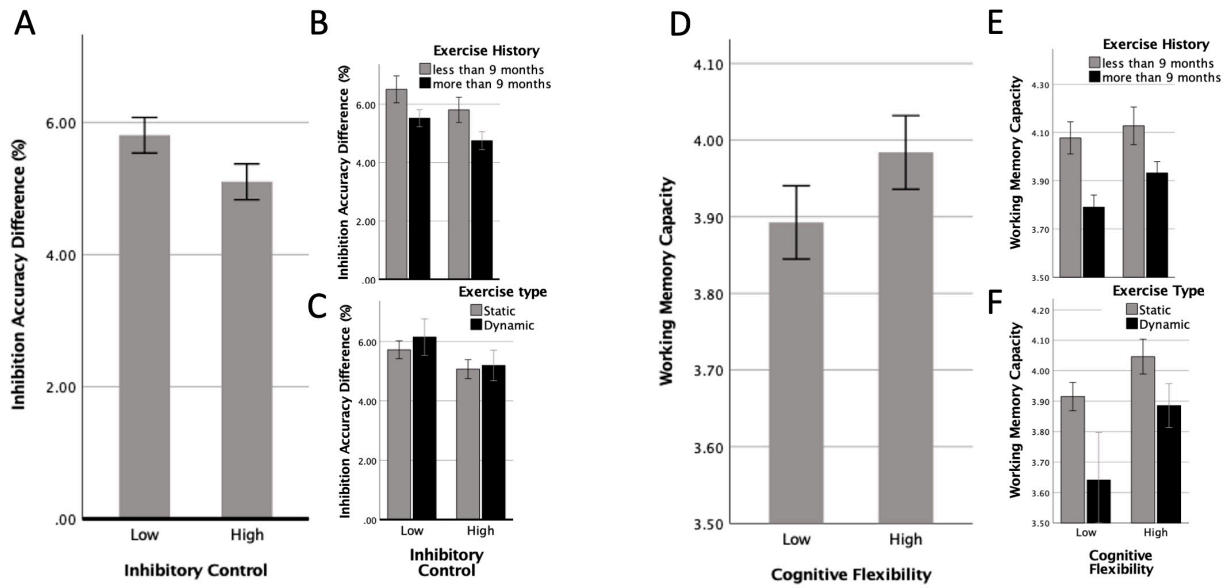

Figure 4 Executive function performance by exercise history and type

(A) Estimated inhibition accuracy for participants who reported their exercise as high vs. low in inhibitory control. Panel B shows the same effect interacting with exercise history, and Panel C shows the same effect interacting with exercise type. (D) Estimated working memory capacity for participants who reported their exercise as high vs. low in cognitive flexibility. Panel E shows the same effect interacting with exercise history, and Panel F shows the same effect interacting with exercise type. Error bars are 95% confidence intervals.

Discussion

Self-reported executive function use during exercise was predictive of executive functioning, as measured by the flanker and the backward span task. However, the data did not show blanket support for correlations between self-reports of executive function use in regular exercise and performance on laboratory measures. Rather the data supported the primary hypothesis regarding the near transfer of specific components of executive functioning to measures of laboratory tasks. For instance, when participants reported that their primary exercise required greater inhibitory control, the data showed they also tended to perform more efficiently on the flanker task, a well-established measure of inhibitory control. And when participants reported that their primary exercise required high levels of cognitive flexibility, the data showed they tended to have higher estimates of working memory capacity on the backward span, a well-established measure of cognitive flexibility.

This pair of findings suggests that the positive relationship between exercise and executive function holds for participants who engage in exercise activities that are perceived to make specific demands on inhibitory control and cognitive flexibility. Conversely, it implies that participants who engage in exercise activities that are not perceived as demanding of executive functioning tend to perform more poorly on the

2. There was missing data for one participant who omitted two questions about executive function use during leisure, and for another participant who did not report leisure intensity. Rather than excluding these participants full information maximum likelihood estimation was used.

corresponding laboratory tasks. These results are therefore strong correlational support for the cognitive engagement hypothesis, because regular exercise reliant on specific components of executive functioning were found to predict better performance on laboratory tests aimed at those components.

The third hypothesis regarding the generality of these results to non-exercise leisure activities in these same participants' lives was not supported. When the same analyses were conducted on participants self-reports of cognitive engagement in non-exercise leisure activities, there was no relationship between the executive function demands of those activities and the laboratory tests. This finding argues against the possibility that people with relatively better executive functioning simply seek out activities that capitalize on those strengths. They data showed that if they do so for exercise activities, they do not do the same for non-exercise leisure activities. The possibility of dispositional overlap on two or measures commonly faces correlational studies of exercise and cognition (Jacobson & Matthaeus, 2014; Sakamoto et al., 2018; Wang et al., 2013). Yet, there was no evidence in the present data that reports of executive function use during non-exercise leisure activities predicted performance on the flanker task or backward span. Leisure qualifiers (history, duration, intensity and type) were also not generally predictive in the SEM model. These absent correlations suggest that the exercise-dependent correlations we have observed are not simply reflecting a broader tendency for people with certain executive function abilities to seek out activities that are demanding of those functions.

Why do cognitively engaging leisure activities not predict performance on laboratory measures of executive functioning? A possible distinction is that exercise uniquely activates neurophysiological factors such as brain volume, neuroplasticity, neurogenesis, and cerebral blood flow (Heisz et al., 2017; Hyodo et al., 2016; Yanagisawa et al., 2010) that lead to structural changes in the brain. Thus, even if exercise and leisure are comparable in their reliance on executive functioning, exercise may have an advantage through its unique contributions through these pathways.

Limitations

It is important to note that exercise history, duration, intensity and type were not significant predictors in the SEM model, although exercise type and history were significant predictors of laboratory performance based on the parameters estimated by the SEM models. One reason these relationships were not seen more strongly here is that our participants were university students and these effects are stronger when there is a relatively longer history of exercise (Etnier et al., 1997) and when participants are not at their peak developmental period (Voss et al., 2011).

We also acknowledge that the present results are premised on a two-factor measurement model of executive function use during exercise: inhibitory control and cognitive flexibility. This model was identified in a data-driven way and so is highly specific to this data set. We therefore note several caveats. First, reverse worded items were not predictive in the construction of this model, resulting in more statistical noise than useful signal. In contrast to the 15 positively worded items which all correlated positively with their dimensions (14 item significantly so), only seven of the negatively worded items correlated negatively, as they were expected to, and they correlated less strongly than the positive items. Six other negative items were near zero in their correlations (I4, I8, I10, C10, W6, W8), and two items were weakly positively correlated (C4, C8). Our interpretation is that participants had a harder time interpreting these items with respect to the positively worded rating scale (ranging from *never* to *always*).

Second, we collapsed working memory and cognitive flexibility into one dimension we called cognitive flexibility for two reasons; a majority of items from that dimension loaded onto it and because the two working memory items that loaded on this factor (W3, W5) seemed to relate to flexible thinking as much or more than the control of working memory. A strong theoretical interpretation of this finding might be that the three-factor model of executive functioning favored by Diamond (2013), Miyake et al. (2000), and others is wrong. However, we think this is premature, given the nature of our unvalidated 30-item self-report questionnaire that is focused solely on regular exercise and leisure activities. It seems more likely that participants found these concepts hard to distinguish from one another in their subjective reports. The finding may also be peculiar to this participant sample. To address these concerns, we tested this model in an independent sample in study 2 and at the same time used two different standard laboratory tasks: one measuring inhibitory control (stop-signal task) and one measuring cognitive flexibility (trail making B).

Study 2

This study built on Study 1 in two ways. First, it was an opportunity to test the two-factor structure of executive function use during exercise identified in study 1 within an independent data set. Second, Study 2 used different executive function tasks, the stop-signal task and trail making B.

The stop-signal task measures a form of inhibitory control sometimes called action cancellation. Participants who regularly exercise have shown better inhibitory control on this task (Padilla et al., 2013, 2014), as have dynamic athletes over athletes from static sports and non-athletes (Wang et al., 2013), and, as have expert soccer players over novices (Beavan et al., 2020; Hagyard et al., 2021).

The trail making B task is a completion-time based measure of cognitive flexibility (Hobert et al., 2011; Sánchez-Cubillo, 2009). Trail making B times are reported to be shorter for athletes of greater skill from those of lesser skill (Han et al., 2011), is reported to improve following a session of exercise (Harveson et al., 2016; Murray & Russoniello, 2012), and is sensitive to exercise intensity (Tierney et al., 2010).

The primary predictions, following from the cognitive engagement hypothesis, were that participant's reports of inhibitory control during exercise would predict stop-signal task performance as well as errors made during trail making, and that participant reports of cognitive flexibility during exercise would predict faster trail making completion time. As in Study 1, participants also answered questions about their leisure activities, which the cognitive engagement hypothesis would not expect to predict executive function.

Method

Transparency and openness

This study was not preregistered. We report a priori power analyses for the sample size. All of the data files and the statistical code used to analyze the data in this study are posted here: https://osf.io/cse4t/?view_only=2125834d3a894994aedef0866ac7c2ee.

Estimated sample size

Following MacCallum et al. (1996), we estimated that a sample of 200 resulted in an estimated power of .69, given α = .05, ε_o = 0.07, ε_a = .10 and df = 34. Increasing the sample to 300 resulted in an estimated power of .86. We therefore sought a sample size falling between the bounds of 200-300. The final sample size was 243 for an estimated post hoc power of .80.

Participants

Participants were recruited through the University of British Columbia human study participant pool, following review and approval of the research plan by the University of British Columbia Behavioral Research Ethics Board (H18-03515). A total of 299 participants completed the study, and among these 243 reported exercising. All participants completed the study within an hour and were provided 1% course credit. Participants were excluded if their exercise or leisure history was less than 1 month, and one participant was also excluded for listing an identical activity for both exercise and leisure. This left 227 in the exercise data set and 290 in the leisure data set, with 220 engaging in both exercise and leisure activities.

Participants who exercised were on average 20.40 years old (*SD* = 3.10), the majority were women (77.53%) and most identified as East Asian (45.37%), followed by European/Caucasian (26.43%), Indian-South (11.01%), Other (9.69%), Middle Eastern (2.64%), Latin American (2.20%), Native American (1.32%), African (0.88%), and opting to not answer (0.44%). Figure 5A shows the relative frequency of various exercise activities. Participants reported an average exercise history of 7 months, with an average of 60 to 90 minutes of per week, and an average intensity of moderate.

Participants who reported a primary leisure activity had very similar characteristics because most of them also reported exercising. Figure 5B shows the relative frequency of various leisure activities, with the most popular being viewing, listening to music and reading. Participants reported an average leisure history of 9 months, with an average of 90-120 minutes per week, and an average intensity of low.

Procedure

The procedure followed that of Study 1, with two exceptions: (1) participants completed only the positively worded items identified in Study 1 for both exercise and leisure activities, and (2) laboratory testing consisted of the stop-signal task and trail making B task, with task order randomized.

Self-report measures

The negatively worded items were not included in Study 2, both because they did not contribute to a good-fitting model, and because we were looking to reduce the time taken in answering the self-report questions. The stop-signal and trail making B tasks together more time to complete than the tasks in Study 1. Thus, to balance the limited one hour period we had with each participant, along with the added time needed for the new tasks, we administered only the positively worded items. We retained the 10 items comprising the model supported by Study 1 along with the five other positive items, just in case Study 2 pointed to a model with a different factor structure.

Laboratory measures

These tasks were programmed using the Matrix Laboratory (MatLab), along with the *Psychophysics Toolbox* (Brainard, 1997; Kleiner et al., 2007). The stop-signal task measures a form of inhibition called action cancellation. Performance on this task is often described as a race between the go process and stop process where the winner of this races determines if an action is completed or canceled (Logan & Cowan, 1984; Verbruggen et al., 2019). The main outcome of the stop-signal task is the stop-signal reaction time (SSRT). The present stop-signal task in this study was modelled after Wang et al. (2013) and Muggleton et al. (2010). The stop-signal task consisted of three phases: baseline, calibration, and testing. Participants first completed 50 baseline trials in which they received only go-signals. The go-signal on these trials was a white circle that appeared on a black computer screen. Participants pressed "*Z*" with the left hand when this white circle appeared to the left of center and "*/*" with the right hand when it appeared to the right. They were instructed to respond as quickly and accurately as possible. The order of events included a fixation cross for 500 ms, a blank black screen for 200 ms, followed by the target, which remained on the screen until a response was made. Mean RT and accuracy were displayed to participants following these 50 baseline trials.

Participants completed 32 calibration trials, with 24 go trials and 8 stop trials. Stop trials were like go trials except they included the appearance of a stop signal in the form of a central white circle. When this stop signal appeared, participants were instructed to immediately stop all keyboard responses. Stop trials ended 2 seconds after the appearance of the stop signal (action cancellation; inhibition success) or after a keyboard response (action noncancellation; inhibition failure). The period of time between the go-signal and the stop-signal is known as the stop-signal delay (SSD) and was initially set to 170 ms. To discourage inten-

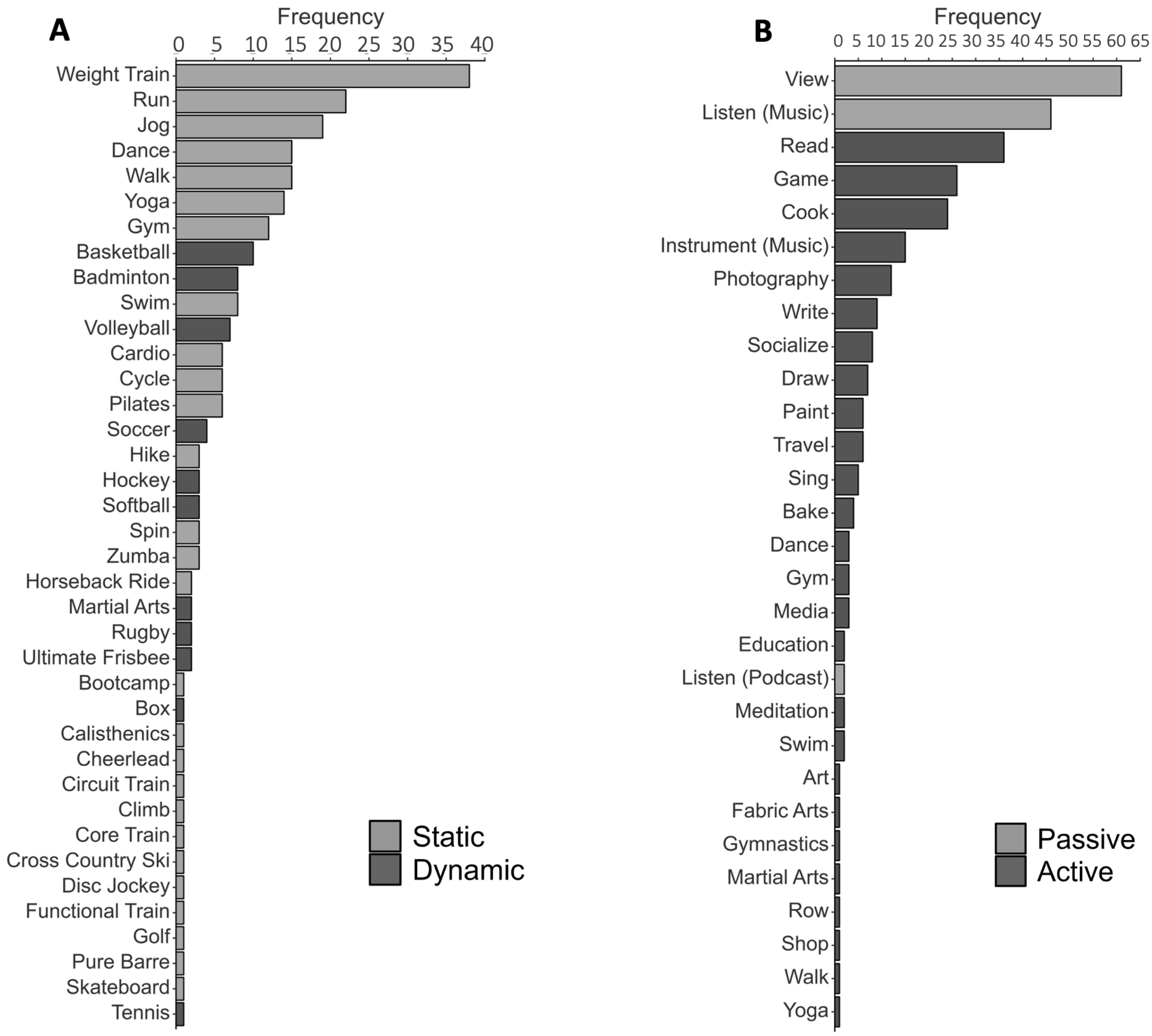

Figure 5 Self-reported exercise

The relative frequency of reported primary exercise (panel A) and leisure (panel B) activities in Study 2. Type of exercise (dynamic, static) and leisure (active, passive) is shown in colour. See text for description of how the type was determined.

tional slowing in anticipation of a stop-signal, RTs on Go trials had to be faster than the mean RT a participant had achieved during the baseline trials with a tolerance of three standard deviations. Slower responses prompted a screen message to "act as quickly and accurately as possible" for 1,750 ms.

After finishing a block of trials, participants were given on-screen feedback about their mean RT and accuracy, along with a message that the next set of trials would be easier (or harder). False Go responses were used to calculate a noncancelled error rate. This rate represented the proportion of trials in which a stop signal appeared, but participants still made a keyboard response. If this rate exceeded .625, then the time between go-signal and stop-signal (SSD) on the next set of trials was shortened by 40 ms, thereby allowing more preparation time for the participant. If this rate was less than .375, then the SSD on the next set of trials was lengthened by 40 ms. If this rate fell between these bounds, the SSD remained the same. The calibration phase ended when participants achieved a noncancelled error rate between .375 and .625 for two consecutive blocks. The testing phase began immediately after the calibration phase and consisted of 108 go trials and 36 stop trials. Stop trials were further broken down such that 12 were at the SSD determined in the calibration phase, 12 were 40 ms less than this SSD, and 12 were 40 ms more than this SSD.

An estimate of stop-signal reaction time was calculated for each participant using their distribution of correct go RTs, noncancelled error rates, and SSDs from the testing phase (Muggleton et al, 2010; Verbruggen et al., 2019; Wang et al., 2013). Briefly, if a participant had an SSD of 100 ms and a noncancelled error rate of .45, this would suggest that, for this given delay 45% of the time, this participant's go process was faster than their stop process. In this example, the go RT nearest the 45th percentile would be identified within the correct go RT distribution and subtracted by 100 ms to measure this participant's stop signal reaction time. This process was completed for each SSD (critical, + 40 ms and -40 ms) where the noncancelled error rate fell between .15 and .85, with the resulting SSRTs averaged into a single mean SSRT (also sometimes called $SSRT_{av}$; Verbruggen et al., 2019) [3].

Figure 6 depicts outcomes from the stop-signal task, including correct go RTs, noncancelled RTs, and the mean SSRT. As expected, RTs were faster during baseline trials (a stop signal never appeared), followed by noncancelled trials, and they were slowest on trials where a stop signal could appear but did not. Also as expected (Wang et al., 2013), the noncancelled error rate on test trials increased as the SSD was elongated.

The second executive function task was trail making B. During this task participants tried to connect spatially dispersed numbers and letters in alternating order (e.g., 1-A-2-B-3-C) on a computer screen, using a mouse. Each trial began with the number 1 presented randomly on the screen. Once the participant clicked on its location, all the remaining numbers and letters appeared in random locations. Participants then clicked on the next target (e.g., the letter A), which prompted a line to connect the A to the previous target (1). This process was repeated until all targets had been clicked. Numbers and letters were in consolas font (size 40), and a correct click fell within a 20-pixel radius of the current target. Participants completed one practice trial from 1 to D prior to testing.

Participants completed a total of five trials for targets from 1 to M. Target locations were randomly determined with the constraint that the target could not overlap. Completion times for these five trials were averaged to calculate mean trail making completion time. Errors (any click outside a 20-pixel radius) were also summed across all five trials. The mean completion time in the current study was approximately 60 seconds, and errors per trial averaged around 5. Note that many other measures are possible with this computerized trail making test, but they fall outside the scope of this study.

Results

Exercise results

As in Study 1, a 10-item measurement model was fit to the exercise data. An assessment of the internal consistency of the 10 items yielded Cronbach's alpha = .86. Mean ratings and standard deviation on the 10 exercise items are summarized in Table 6 of the appendix. This model yielded a significant Chi-square, χ^2 (34) = 113.09, p < .001, it showed medium-to-acceptable-fit, RMSEA = .10, 90% CI [.08, .12], CFI = .91, SRMR = .07. Additional exploration including all 15 positively

3. Two participants had noncancelled error rates outside of .15 and .85 for all three SSDs. For these two participants their SSRT was calculated based on their performance during the final two blocks of the calibration phase.

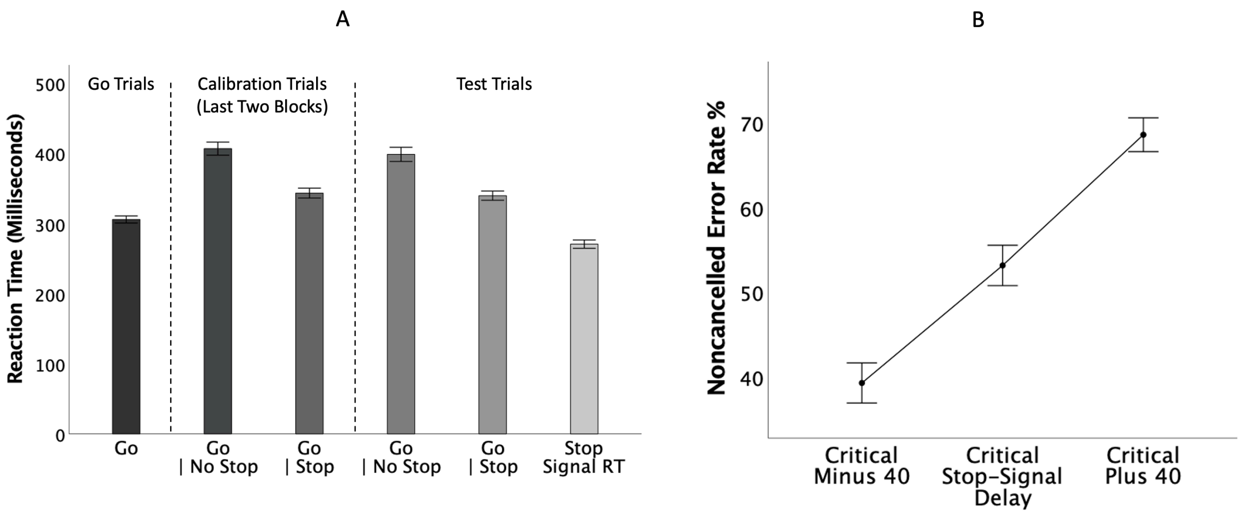

Figure 6 Executive function performance

(A) Mean reaction times in the baseline, calibration, and test phases of the stop-signal task in Study 2. (B) Mean percentage of noncancelled error rates in the three stop-signal delay conditions in Study 2. Error bars in A and B are +/- 1 standard error of the mean.

worded items did not yield a better-fitting model, and so we moved forward with SEM modeling.

Figure 7 shows the structural equation model, which combined the two factor scores derived from the 10-item exercise measurement to predict performance in the laboratory tasks. The main findings were that exercise reported to rely on inhibitory control predicted faster stop-signal reaction time, β = -.24, *B* = -14.82, 95% CI [-28.45, -.1.20], *p* = .033 and fewer trail making errors, β = -.27, *B* = -11.53, 95% CI [-21.39, -1.67], *p* = .022, but did not predict faster trail making completion time, β = -.21, *B* = -4.56, 95% CI [-9.15, .03], *p* = .051. Exercise reported to rely on cognitive flexibility predicted slower stop-signal reaction time, β = .22, *B* = 13.15, 95% CI [1.52, 24.79], *p* = .027, and slower trail making completion time, β = .30, *B* = 6.22, 95% CI [2.24, 10.20], *p* = .002, but did not predict trail making errors, β = .17, *B* = 7.14, 95% CI [-1.20, 15.48], *p* = .093. This pattern of results corresponds to the pattern discovered in Study 1.

A number of exercise qualifiers were associated with the laboratory tasks. Namely, participating in dynamic exercise predicted faster stop-signal reaction time, β = -.18, *B* = -19.37, 95% CI [-33.70, -5.04], *p* = .008, and faster trail making completion time, β = -.17, *B* = -6.14, 95% CI [-10.99, -1.29], *p* = .013. Longer exercise history predicted slower trail making completion time, β = .16, *B* = 1.96, 95% CI [.44, 3.48], *p* = .012. The model yielded suboptimal fit to the data, as evidenced by a significant Chi-square, χ^2 (98) = 307.45, *p* < .001, with alternative fit indices being, CFI = .82, RMSEA = .10, 90% CI [.08, .11], SRMR = .13. Applying a Satorra and Bentler (1994) correction for non-normality did not greatly alter parameter estimates. One exception was that exercise reported to rely on inhibitory control no longer predicted trail making errors, β = -.27, *B* = -11.53, 95% CI [-24.20, 1.13], *p* = .074.

We again examined the effect sizes identified by the SEM model by comparing model-estimated parameters for participants who scored low versus high on each dimension using a median split. Figure 8A shows this for the link between mean stop-signal time and inhibitory control: participants rating their exercise high in inhibitory control had values that were signif-

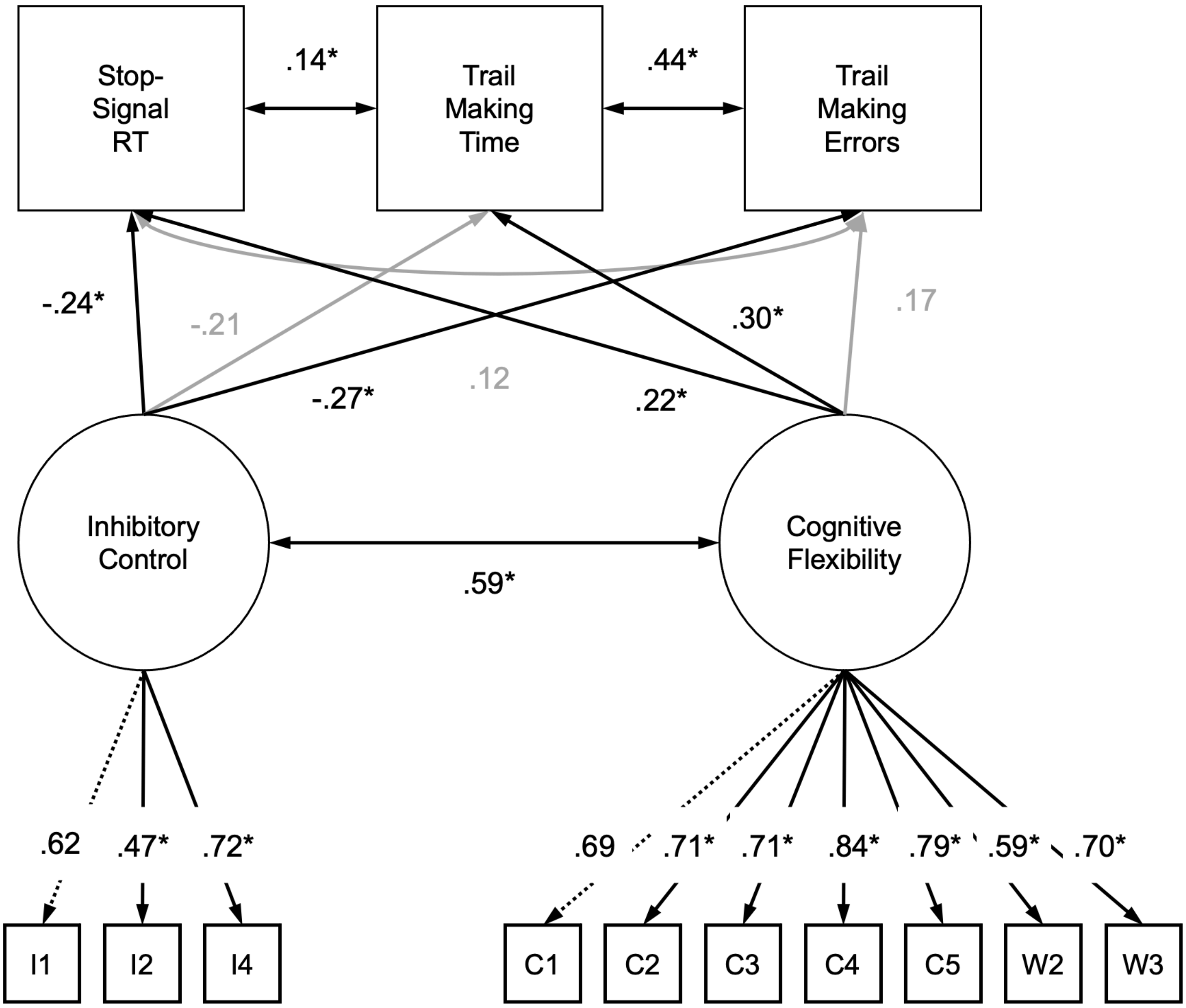

Figure 7 Linking exercise self-reports to performance

The best-fitting structural equation model in Study 2, showing the relations between exercise qualifiers in the top row, the two latent constructs identified by confirmatory factor analysis in the middle row, and the 10 items that loaded significantly on the two latent constructs in the bottom row.

icantly faster (*M* = 270 ms, *SE* = 0.98 ms) than participants rating their exercise as low in inhibitory control (*M* = 275 ms, *SE* = 0.87 ms), $t(225) = 3.40$, $p < .001$, Cohen's $d = 0.451$. The link between cognitive flexibility and mean stop-signal time was not significant, $p >$ 7.

A similar examination of trail making errors in Figure 8D showed that participants rating their exercise high in inhibitory control had mean trail making errors that were significantly fewer (*M* = 21.3, *SE* = 0.41) than participants rating their exercise low in inhibitory control (*M* = 26.1, *SE* = 0.39), $t(225) = 8.44$, $p < .001$, Cohen's $d = 1.12$. Trail making time was also longer for participants rating their exercise high in cognitive flexibility (*M* = 63.08 s, *SE* = .37) than those who rate their exercise low in cognitive flexibility (*M* = 60.67 s, *SE* = .31), $t(225) = 5.02$, $p < .001$, Cohen's $d = .67$.

We again examined the exercise qualifiers of history and type in this model. With regard to exercise history (Figure 8B), stop-signal times were significantly slower for participants reporting a longer exercise history (*M* = 275 ms, *SE* = 0.770) than a shorter history (*M* = 269 ms, *SE* = 1.130), $F(1, 223) = 14.48$, $p < .001$, $np^2 = 0.061$. When this factor was combined with a median split on inhibitory control, each of the main effects were significant ($p < .001$) and there was no interaction ($p > .46$).

Figure 8C shows that participants engaged in dynamic regular exercise had faster stop-signal times (*M* = 263 ms, *SE* = 1.31) than participants engaged in static exercise (*M* = 275 ms, *SE* = 0.631), $F(1, 223) = 71.76$, $p < .001$, $np^2 = 0.243$. The same pattern held for trail making completion times. Participants engaged in dynamic regular exercise had faster trail making times (*M* = 59.7 sec, *SE* = 0.583) than participants engaged in static exercise (*M* = 62.4 sec, *SE* = 0.270), $F(1, 223) = 18.75$, $p < .001$, $np^2 = 0.078$. When these factors were combined with median split on inhibitory control, each of the main effects were strongly significant ($p < .001$) and there were no interactions ($p > .20$).

Leisure results

A structurally identical 10-item two-factor model was fit to the leisure report data. This model yielded a significant Chi-square, χ^2 (34) = 109.88, $p < .001$, and showed acceptable fit on alternative fit indices, RMSEA = .09, 90% CI [.07, .11], CFI = .95, SRMR = .05. No variables in this model predicted executive functioning task performance. Among the paths with the largest standardized beta coefficients, leisure reported to rely on inhibitory control did not predict trail making completion time, $\beta = -.21$, $B = -2.76$, 95% CI [-6.21, .69], $p = .117$, or trail making errors, $\beta = -.15$, $B = -4.02$, 95% CI [-10.90, 2.85], $p = .251$, or SSRT, $\beta = .12$, $B = 4.64$, 95% CI [-5.22 14.50], $p = .356$. Leisure reported to rely on cognitive flexibility did not predict trail making completion time, $\beta = .12$, $B = 1.65$, 95% CI [-1.79, 5.09], $p = .348$. The overall model had a significant Chi-square, χ^2 (98) = 401.90, $p < .001$, with alternative fit indices being, RMSEA = .10, 90% CI [.09, .11], CFI = .83, SRMR = .16.

Discussion

Self-reports of executive function use during exercise predicted performance on the stop-signal and trail making B task. Participants who reported that their exercise relied on inhibitory control tended to have faster stop-signal reaction times and made fewer trail making errors. The results of study 2 did not find leisure activities to predict executive functioning in a similar way. Yet is important to note that not all the results supported the cognitive engagement hypothesis. Most notably, participants who reported that their exercise relied on cognitive flexibility were less accurate in action cancellation and had slower trail making times.

The findings for inhibitory control in both studies 1 and 2 supports previous findings that this component of executive functioning may be the most sensitive to exercise-related improvement (Hsieh et al., 2020; Soga et al. 2018; Liu-Ambrose et al., 2010). Cognitive flexibility in hindsight, may have resulted in slower trail making through the employment of inefficient strategies. While some aspects of cognitive flexibility may be beneficial for trail making B (e.g., efficient shifts in task set), others may be deleterious (e.g., innovation and creativity). These latter aspects might slow trail making completion times, if, for example, participants are overthinking in their search for a hidden pattern or some underlying structure in the display that is not actually present. Such overthinking might contribute to slower response times during a search for successive symbols that are positioned randomly on the screen.

The exercise qualifiers of history, duration, intensity, and type in study 2 also revealed some findings worth discussing. First, participants exercising in dynamic environments tended to have faster stop-signal reaction times and trail making completion times when compared to those in static environments. In a previous study, Wang et al. (2013) reported that athletes

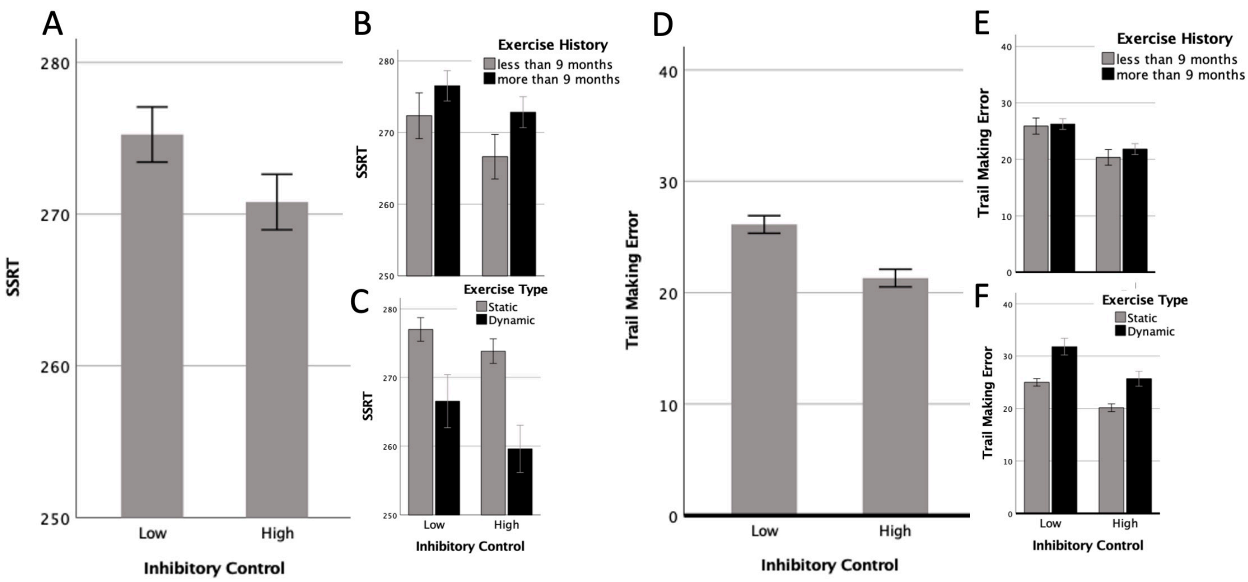

Figure 8 Executive function performance by exercise history and type

(A) Estimated stop-signal response time (SSRT) for participants who reported their exercise as high vs. low in inhibitory control. Panel B shows the same effect interacting with exercise history, and Panel C shows the same effect interacting with exercise type. (C) Estimated trail making errors for participants who reported their exercise as high vs. low in inhibitory control. Panel D shows the same effect interacting with exercise history, and Panel C shows the same effect interacting with exercise type. Error bars are 95% confidence intervals.

from dynamic sports (tennis) had faster stop-signal reaction times than athletes from static sports (swimmers) and nonathletes, supporting the idea that inhibitory control is associated more strongly with dynamic exercise activities (Heilmann et al., 2022). Second, participants reporting longer exercise histories tended to have slower trail making completion time. On the face of it, this outcome is contrary to the idea that a longer exercise history is beneficial for all executive functioning (Padilla et al., 2013, 2014), though it may also reflect the degree to which a given exercise can remain novel and challenging, a speculation worth pursuing in future research.

General Discussion

The claim that cognitive engagement during exercise is beneficial for cognition has been made previously in studies of older adults (Tomporowski, 1997), in studies of children (Best, 2010; Diamond & Ling, 2016), and by neurophysiologists speculating on hippocampal neurogenesis in the aging brain (Fabel & Kempermann, 2008). The present study tested this cognitive engagement hypothesis with a correlational individual-differences methodology, looking for links between self-reported executive function use in participants' regular exercise and their performance on laboratory tests of these functions, in two independent samples of participants.

Rather than trying to find an a priori definition of cognitive engagement, we asked participants to indicate how much their primary exercise made demands on their executive functions. We did this by having participants provide ratings on statements that characterize the mental requirements of their primary exercise, with the statements inspired by three components of executive function: inhibitory control, cognitive flexibility, and, working memory (see the references associated with each item in Table 1). Then we submitted these responses to a confirmatory factor analysis in order to find a good fitting measurement model. The results showed support for two components: inhibitory control and cognitive flexibility.

In a second phase, participants performed two laboratory tasks that are often used to assess executive function. A structural equation model was built to see whether the constructs identified by confirmatory factor analysis predicted participants' performance on these two laboratory tasks. The results showed that when participants reported that their exercise relied on inhibitory cognitive control, they performed better on a flanker task, which requires active ignoring of distracting information. When their exercise demanded cognitive flexibility, they performed better on a backward digit span task, which requires the active manipulation of mental information.

In a second study, we tested an independent sample of participants and two different executive function tasks (stop-signal, trail making B). The results supported the predictive validity of the inhibitory control factor, (i.e., reports of the need for inhibitory control in a participant's regular exercise predicted their performance on the stop-signal task). There was some support, though weaker, for the predictive validity of the cognitive flexibility component (i.e., there were fewer trail making B errors). A comparison of studies 1 and 2 also showed that the two-factor exercise model in study 2 showed a poorer fit than the same model in study 1. A reduced fit here is not entirely surprising, given the exploratory and data-driven approach used in study 1, which was able to overfit the data by capitalizing to some degree of measurement noise. Future studies would do well to replicate each of the studies in detail (i.e., testing the same laboratory tasks in a new sample of participants), rather than trying to generalize from one set of tasks in Study 1 to a new set of tasks in Study 2.

In both studies, we also tested the specificity of the findings for exercise, by repeating the procedures for participants' non-exercise leisure activities. The exercise-related associations we observed with executive function measures were not found for these self-reports of leisure activities, ruling out the possibility that the correlations we observed were more general dispositional characteristics of the participants. Taken together, these findings support the more focused claim that when an exercise is perceived to depend more heavily on a specific dimension of executive functioning, then it predicts relatively better performance on a laboratory measure of that specific dimension. At least this was the finding for the inhibitory control dimension. It was less strongly so for the cognitive flexibility dimension, and it was absent for working memory.

Implications

At a global level, these findings are consistent with much research over the past few decades supporting the idea that exercise contributes significant positive effects to the cognitive functioning of healthy young adults (Ludyga et al., 2020; Voss et al., 2011). At the same time, we hasten to note that these effects tend not to be as large, nor as robust, as those that can be found in samples of individuals who are not at the peak of their cognitive and athletic development, including children, aging adults, and individuals with cognitive impairments through trauma or disease (Voss et al., 2011). However, where the present findings contribute most to past results is in the emphasis they place on the specificity of the transfer between exercise and cognition. This point can be contrasted with the conclusions of Ludyga et al. (2020), who after conducting a meta-review of 80 studies using randomized controlled trials, concluded that "the effect of exercise on cognition appears to be general rather than selective, as effect sizes did not differ significantly between the assessed cognitive domains" (p. 605). However, that study compared the benefits of various types of exercise quite generally to various dimensions of executive functioning. It did not look for specific associations between dimensions of executive functioning and related laboratory tasks. And how could it have? There is currently no agreement on which exercise activities link specifically to which dimensions of executive functioning. Here we broke that impasse by asking participants directly to indicate the demands their exercise made on the various dimensions.

A central finding emerging from Ludyga et al.'s (2020) review that is also consistent with the present finding is the finding of larger benefits of "exercise on cognitive function after coordinative exercise compared with other exercise types" (p. 603). It seems reasonable that coordinative exercises such as running and dribbling a soccer ball with the feet or a basketball with the hands place greater demands on inhibitory control and cognitive flexibility than exercises that focus more exclusively on aerobic fitness or strength training.

Although the present studies were designed to detect relationships between all three components of executive function - inhibitory control, cognitive flexibility, and working memory - the inhibitory control component showed the most consistent associations across the two studies. Study 1 showed that for undergraduate students, exercise that made greater demands on inhibitory control predicted a smaller accuracy difference between congruent and incongruent trials on a flanker task. Study 2 found this same exercise-specific relationship in a different group of undergraduate students, exercise that made demands on inhibitory control predicted faster stop-signal reaction time and fewer trail making errors. This means that the exercise reported to rely on inhibitory control was linked to three distinct facets of this construct, including the control of interfering distractors (flanker task), the cancellation of prepared actions (stop-signal task), and control over impulsivity (trail making B).

The predictive strength of inhibitory control over other executive functions is supported by recent reviews. A review of high-intensity interval training by Hsieh et al. (2020) and a study of resistance training by Soga et al. (2018) both reported that these forms of exercise were linked to improvements in inhibitory control more consistently than cognitive flexibility and working memory. In a related study, Liu-Ambrose et al. (2010) compared older adult women assigned to either weekly resistance training or to balance and tone training. After 12 months, participants in both groups showed comparable cognitive flexibility (as assessed by trail making tasks) and working memory (as assessed by a digit span task), but participants assigned to resistance training showed greater inhibitory control than those that completed balance and tone training (as assessed by reduced interference in a Stroop task).

The neurophysiological account of the exercise-cognition link also provides perspective on why the association between leisure and executive functioning may not be as strong. First, leisure activities may not influence cerebral blood flow to the same degree as exercise. For example, Yanagisawa et al. (2010) found that an acute bout of exercise improved inhibitory control on a Stroop task (i.e., less interference) and that this increase in performance coincided with greater cerebral blood flow within the left dorsolateral prefrontal cortex, implicated in more efficient inhibitory control. Second, leisure activities may not lead in the same way to the cascade of consequences that stem from an increase in neurotrophic factors such as BDNF (Erickson et al., 2012).

Limitations and future directions

The first limitation to note in this study concerns the participant sample and the range of activities they reported as their regular exercise. A young adult sample of students at a large state-funded university limits the generality of the findings to this cohort. Their most frequently reported exercises were running, weight training, and gym in study 1 and weight training, running/jogging, and dance/yoga in study 2. Both of these factors conspire to make this a fairly conservative test of the cognitive engagement hypothesis. Given the vast extant literature on exercise-cognition links reviewed in the introduction, the hypothesis would have a better chance of finding support in studies of participants who are not at their peak development (Voss et al., 2011) and in participants who engaged in a wider range of activities (Ludyga et al., 2020).

A second limitation to consider is that our assessment of the executive functioning involved in a participant's regular exercise was based on self-report. Along with the strengths of this approach, we highlighted in the introduction (e.g., being able to take into account individual differences in types of exercise, the variety of settings, levels of engagement, and the diverse conditions under which exercise occurs) there are also weaknesses. One of them is that participants may not have equally good self-awareness of the involvement of executive functioning in their exercises. Another is that some dimensions may lend themselves to self-report more readily than others. For example, given the present results, it may be easier to access the inhibitory control dimension in a subjective report than the working memory dimension. Future research might compare these methods with more implicit measures (e.g., content analyses of participants' spontaneous descriptions of exercise scenarios) or even consider third-party observational measures (e.g., coaches or other athletes on the same team).

The SEM models in both studies provided less than perfect fits to the data, by both absolute (RMSEA, SRMR) and relative (CFI) criteria. This means that substantial variance in the laboratory tasks measuring executive functions was not predicted by the latent variable structure in the self-report data. This is not surprising, given that executive functioning is affected by many factors, especially in a university student sample that is engaged in many activities that can influence executive function both positively (e.g., studying) and negatively (e.g., partying). For example, a recent study reported that having college students engage in emotional regulation strategies while performing a set-switching laboratory task, which indexed both inhibitory control and set-shifting abilities, interfered most with the inhibitory control measure (Koay & Meter, 2023). These findings were more pronounced following a negative mood versus a positive mood induction procedure. The modest fit of the SEM models may also reflect the limitation of assessing executive functioning in exercise from self-reports. Yet we are encouraged that these self-reports were able to predict the dimensions of inhibitory control and cognitive flexibility, despite all these barriers, to the extent they did across two studies.

The present study measured executive functions using indices of speed and accuracy for some tasks (flanker task in Study 1, trail making B tasks in Study 2), but it measured only accuracy for the backward span task in Study 1 and only speed for the stop-signal task in Study 2. There is now growing awareness, emerging from studies of attentional control theory (Eysenck et al., 2007), that the efficiency with which a task is completed (typically using speed measures) is somewhat separable from the effectiveness of the task (typically measured with accuracy). For example, anxiety and threat have adverse effects on performance that are revealed more clearly in measures of processing efficiency than of effectiveness, leading to calls to include both kinds of measures in studies of executive function whenever possible (Brimmell et al., 2022). Future research could profitably assess both efficiency and effectiveness more even-handedly when comparing across dimensions of executive function.

We may have also jettisoned the negatively worded items too hastily. We did so after Study 1 because of their bad initial fit to the measurement model and because we needed to save some time for participants in Study 2 to perform the new executive function tasks. But this meant that Study 2 differed from Study 1 in several ways and so different model outcomes in the two studies could not be interpreted cleanly. Future research may profit from replicating Study 1 procedures in full with an independent set of participants and by including all 30 items (or even more if time allows) in a replication of Study 2.

Our trail making B task in Study 2 was a novel implementation on a computer screen of a very popular pencil and paper test. In our version of it, participants did not need to trace the region of space between symbols, but simply made a mouse click on each of the symbols in sequence. This may have made the task more of a visual search and less of tracing task than the traditional paper and pencil test. A full assessment of this in future research will require a comparison between a mouse tracking version of the task and the mouse click version we employed.

A fundamental limitation of the present study is that we were only able to link regular exercise to two of the three most widely discussed components of executive function: inhibitory control and cognitive flexibility. In contrast, working memory was not identified in our studies, despite our best attempts to use laboratory tasks that have been closely aligned with this component in past research (i.e., backward digit span and trail making B). This may have been because our exercise items were not sufficiently targeted to this construct, despite our best efforts to use concepts and phrases that are frequently used in the executive function literature. Or it may simply be the case that working memory is too overlapped with cognitive flexibility during exercise. Yet another possibility is that the working memory concept is not as accessible to self-report, meaning that it contributes least to participants' metacognitive awareness of their own abilities. Future research will need to disentangle these possibilities.

It is worth noting that the component that linked most robustly to exercise — inhibitory control — was based on three items that map most often onto the facets of inhibitory control in the literature. These include item 1: "slowing down to avoid making mistakes," which is an essential aspect of the stop-signal task; item 3: "filtering and ignoring distracting information," which is closely tied to the requirement of the flanker task; and item 7: "pausing to double check what one is doing," which is the essential requirement for avoiding errors on the trail making B task. This suggests that greater success may come in the future by developing items for the other two components that are more closely tied to the requirements of the laboratory tasks used to measure them. For example, one of the specific requirements of the backward span digit task is that multiple pieces of information must be rearranged mentally before an action can be generated. Perhaps an item referring specifically to "mentally rearranging objects or symbols" would capture this commonality between exercise activities and the laboratory task used to measure working memory.

Finally, we acknowledge that the two-factor model of exercise identified in this work is undoubtedly wrong in many respects, even if it has been useful in showing proof-of-concept support for the cognitive engagement hypothesis. At a minimum, the present findings reveal reliable associations between reports of executive function use in regular exercise and objective laboratory tests of those functions. We offer these findings as inspiration for future studies to refine.

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Competing interests

The authors have declared that no competing interests exist.

Data availability statement

All of the data files and the statistical code used to analyze the data in this study are posted here: https://osf.io/cse4t/?view_only=2125834d3a894994aedef0866ac7c2ee

A Appendix

Table 2
Self-reported exercise history

	Study 1	Study 2
< 1 month	0	0
1-3 months	11	17.6
4-6 months	11	8.4
7-9 months	9	5.7
> 9 months	69	68.3

Self-reported history of exercise in studies 1 and 2. Values indicate percentages of participants reporting exercise history in months.

Table 3
Mean ratings on all exercise items

Exercise measurement item	Mean	*SD*
Inhibitory control		
I1. slow down to avoid making mistakes	2.88	0.97
I2. care most about speed and performing quickly (R)	3.28	1.05
I3. filter and ignore distracting information	3.50	0.91
I4. decide what to do through impulse alone (R)	3.26	1.01
I5. practice self-control and discipline	3.74	0.93
I6. follow every action to completion (R)	2.23	0.84
I7. pause and double check what I am doing	2.96	1.08
I8. start and complete actions without thinking (R)	3.10	0.98
I9. anticipate making fast or sudden adjustments	3.20	1.09
I10. act without self restraint (R)	3.62	0.91
Cognitive flexibility		
C1. adapt and change how things are done	3.50	0.88
C2. have a plan that I stringently follow (R)	2.74	0.96
C3. try to identify new techniques or strategies	3.52	0.97
C4. follow the same routine (R)	2.64	0.91
C5. practice creativity	2.83	1.11
C6. hold the same mindset from start to finish (R)	2.79	0.94
C7. encounter and solve new problems	3.06	1.08
C8. have little-to-no flexibility to modify what I do (R)	3.73	0.97
C9. rely on a diverse skillset	3.11	1.11
C10. think the same thoughts over and over (R)	3.01	0.93
Working memory		
W1. pay attention to many things at the same time	3.12	1.09
W2. understand everything that is happening even when absent-minded (R)	2.68	0.90
W3. make predictions about what will happen next	3.52	0.97
W4. avoid time-keeping (R)	3.00	1.12
W5. connect and combine different ideas	3.17	1.07
W6. do not care about the order in which things happen (R)	3.09	1.01
W7. multitask	2.84	1.22
W8. disengage from what is happening around me (R)	2.84	0.98
W9. monitor what is happening on a second-to-second basis	2.96	1.05
W10. focus all my attention entirely on one thing before moving onto the next (R)	2.78	1.04

Individual mean ratings and standard deviations for the original 30 exercise items in study 1.

Table 4
Factor loadings for all exercise items

Exercise measurement item	I	C	W
I1. slow down to avoid making mistakes	.38[a]		
I2. care most about speed and performing quickly (R)	**-.20**		
I3. filter and ignore distracting information	**.59**		
I4. decide what to do through impulse alone (R)	-.11		
I5. practice self-control and discipline	**.54**		
I6. follow every action to completion (R)	**-.63**		
I7. pause and double check what I am doing	**.50**		
I8. start and complete actions without thinking (R)	.05		
I9. anticipate making fast or sudden adjustments	**.30**		
I10. act without self restraint (R)	-.08		
C1. adapt and change how things are done		.65[a]	
C2. have a plan that I stringently follow (R)		**-.28**	
C3. try to identify new techniques or strategies		**.66**	
C4. follow the same routine (R)		**.29**	
C5. practice creativity		**.67**	
C6. hold the same mindset from start to finish (R)		**-.19**	
C7. encounter and solve new problems		**.69**	
C8. have little-to-no flexibility to modify what I do (R)		**.29**	
C9. rely on a diverse skillset		**.70**	
C10. think the same thoughts over and over (R)		-.04	
W1. pay attention to many things at the same time			.33[a]
W2. understand everything that is happening even when absent-minded (R)			**-.28**
W3. make predictions about what will happen next			**.60**
W4. avoid time-keeping (R)			**-.36**
W5. connect and combine different ideas			**.72**
W6. do not care about the order in which things happen (R)			-.08
W7. multitask			.17
W8. disengage from what is happening around me (R)			-.04
W9. monitor what is happening on a second-to-second basis			**.36**
W10. focus all my attention entirely on one thing before moving onto the next (R)			**-.34**

Item-to-factor loadings for the original 30 exercise items and the three-factor model in study 1. Bolded items denote statistical significance ($p < .05$). Factor I = Inhibition, C = Cognitive flexibility, W = Working memory. [a]Indicator item

Table 5
Factor loadings for best-fitting reduced model in study 1

	Factors	
Exercise measurement item	**Inhibition**	**Cognitive flexibility**
I1. slow down to avoid making mistakes	.60	
I3. filter and ignore distracting information	**.47**	
I7. pause and double check what I am doing	**.70**	
C1. adapt and change how things are done[a]		.63
C3. try to identify new techniques or strategies		**.64**
C5. practice creativity		**.72**
C7. encounter and solve new problems		**.70**
C9. rely on a diverse skillset		**.70**
W3. make predictions about what will happen next		**.54**
W5. connect and combine different ideas		**.74**

Exercise item-loadings in a two-factor model in study 1. Bolded items denote statistical significance ($p < .05$).

Table 6
Factor loadings for best-fitting reduced model in study 2

	Factors	
Exercise measurement item	**Inhibition**	**Cognitive flexibility**
I1. slow down to avoid making mistakes	.61	
I3. filter and ignore distracting information	**.43**	
I7. pause and double check what I am doing	**.75**	
C1. adapt and change how things are done[a]		.69
C3. try to identify new techniques or strategies		**.72**
C5. practice creativity		**.71**
C7. encounter and solve new problems		**.83**
C9. rely on a diverse skillset		**.79**
W3. make predictions about what will happen next		**.59**
W5. connect and combine different ideas		**.70**

Exercise item-loadings in a two-factor model in study 2. Bolded items denote statistical significance ($p < .05$).