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Are trait self-control and self-control resources mediators of relations between executive functions and health behaviors?

Cyril Forestier^{1*†}, Margaux de Chanaleilles^{2†}, Roxane Bartoletti³, Boris Cheval^{4,5}, Aïna Chalabaev², Thibault Deschamps¹

¹Laboratoire Motricité, Interactions, Performance, MIP - UR4334, Le Mans Université, Nantes Université, Le Mans, Nantes, France

²Univ. Grenoble Alpes, SENS, Grenoble, France

³LAPCOS, Université Côte d'Azur, Nice, France

⁴University of Geneva, Geneva, Switzerland

⁵Laboratory for the Study of Emotion Elicitation and Expression (E3Lab), Department of Psychology, University of Geneva, Geneva, Switzerland

*Corresponding author: 7 Avenue Olivier Messiaen, 72000 Le Mans, France; cyril.forestier@univ-lemans.fr; @CForestier PhD (C. Forestier)

 $\stackrel{}{\mathsf{t}C}$.F. and M.d.C contributed equally and share first authorship

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

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Abstract

This study investigated associations between executive functions (i.e., inhibition, working memory, cognitive flexibility) and individual differences in self-control and health behaviors. We examined whether executive functions predict physical activity, sedentary activity, and healthy and unhealthy diets, and whether trait self-control and self-control resources mediate these associations. Three hundred and eighty-five participants completed a questionnaire assessing trait self-control and self-control resources, physical activity, sedentary activity, and healthy and unhealthy diets. They also performed three randomly ordered cognitive tasks, a stop-signal task (i.e., inhibition), a letter memory task (i.e., updating), and a number-letter task (i.e., switching). Structural equation modeling revealed that self-control resources predicted positively physical activity ($R^2 = .08$), negatively sedentary activity ($R^2 = .03$) and positively healthy diet ($R^2=10$). Moreover, trait self-control predicted positively healthy diet ($R^2 = .10$) and negatively unhealthy diet ($R^2 = .19$). Moreover, analyses revealed that switching significantly predicted self-control resources, and highlighted three totally mediated relations between this executive function and physical activity, sedentary activity and healthy diet. However, no evidence was found supporting associations between inhibition and updating, and health behaviors, or relations mediated by self-control for these executive functions. The findings suggest the importance of trait self-control and self-control resources for health behavior adoption and pave the way for studies exploring the role of the executive functions in an affective context. Open materials [https://osf.io/hpsjw/].

Keywords: self-control resources, trait self-control, inhibition, updating, switching, health behaviors

1. Introduction

According to the World Health Organization, physical inactivity and an unhealthy diet are among the most important risk factors for noncommunicable diseases, causing one death every seven seconds and one death every three seconds, respectively (Forouzanfar, Afshin, Alexander, Biryukov, et al., 2016; Lee et al., 2012). Changing these unhealthy behaviors by improving the regularity of physical activity and healthiness of diet could prevent 16 million premature deaths each year (Forouzanfar, Afshin, Alexander, Anderson, et al., 2016). Despite widespread declarations of intention to adopt healthy behaviors, most people fail to reach minimum recommendations (Ford et al., 2011). In this context, some promising conflict resolution models could effectively promote health behaviors (Sniehotta et al., 2014).

Conflict resolution models (e.g., the integrative self-control theory, Kotabe et Hofmann, 2015; the goal-conflict model, Stroebe, 2022) emphasize that health-behavior facilitators (e.g., health-behavior goals, such as an intention to do more physical activity) face barriers (e.g., temptation toward the competing behavior, such as a desire to engage in a sedentary activity), leading to motivational conflicts that need to be resolved (Forestier, et al., 2022a; Rabiau et al., 2006). An adaptative resolution of this conflict (i.e., one in favor of the goal) promotes the health-behavior goal (e.g., going for a run, snacking on an apple). A maladaptive one promotes the competing behavior (e.g., remaining on the couch, snacking on a chocolate bar) (e.g., Gillebaart et al., 2016). Here, self-control is defined as the self-regulation operationalization, by which an individual resolves a motivational conflicts, favoring healthy behaviors. Indeed, some studies showed correlations between self-control and healthy diet and weight control with a small-to-medium effect size (de Ridder et al., 2012, r = .17), and self-control and physical activity (Pfeffer & Strobach, 2018, r = .29).

In 2018, Forestier et al. identified individual differences in trait self-control and selfcontrol resources, as two dimensions independently associated with health behaviors. Despite their importance, self-control resources have been mostly considered in ego-depletion research (e.g., Rouse et al., 2013) and rarely on research on self-control and health behaviors (de Ridder et al., 2018). However, defined as "the objective and subjective amounts of energy available for the self to initiate a self-control act" (Forestier et al., 2022b, p. 21), the self-control resources seem crucial for motivational conflict resolution, and can be assessed through subjective perception of energy availability, or physiological markers (e.g., vagal activity). Accordingly, trait self-control distinguishes individuals with a more or less tendency to successfully resolve motivational conflicts. In parallel, individual differences in self-control resources distinguish individuals with a more or less tendency to experience a high level of self-control resources (Forestier et al., 2018). Authors identified that a remarkable portion of variance (40%) in selfcontrol resources is found at the between-person level (Smolders et al., 2013). In short, individuals with high trait self-control consume a healthier diet than those with low trait selfcontrol; individuals with high self-control resources practice more physical activity, are less sedentary, and eat healthier than individuals with low self-control resources.

Despite these interesting results, Forestier et al. (2018) did not specifically examined the predictors of individual differences in the two self-control dimensions. Some hypotheses on the executive functions have been already put forward that can partly explain the differences in these dimensions (e.g., Hofmann et al., 2012, Table 2). Specifically, inhibition, updating and switching (also called "inhibitory control", "working memory", and "cognitive flexibility" respectively) is likely related to self-control, and individuals with higher executive abilities would, therefore, be good self-controllers (Friese et al., 2011; Hofmann et al., 2011). Moreover, executive functions could operationalize the "self-control capacity" that makes self-control success possible (Forestier, et al., 2022b; Kotabe & Hofmann, 2015). Presumably, for instance, individuals with high inhibition capacity should present high self-control through a better ability to override prepotent responses such as habits or impulses that are incompatible with goals attainment. Likewise, individuals with high working memory abilities could better maintain information in an active, quickly retrievable state and shield this information from distraction. They are therefore better able to use goal-relevant information. Finally, relative to individuals with lower switching ability, individuals with high switching may present high selfcontrol through a high flexibility (opposed to "rigidity"), which allow goal attainment by abandoning suboptimal means and selecting alternative means to reach the same goal (see Hofmann et al., 2011, 2012, for full theoretical discussion). Additionally, structurally and functionally, brain networks in the prefrontal cortex that control executive function, overlap with networks involved in self-control (e.g., right inferior frontal gyrus, Cipolotti et al., 2016; Lopez et al., 2016).

Several assumptions on how executive functions and self-control might interact have been proposed, including the mediation model hypothesis (Hofmann et al., 2012). To date, most empirical self-control studies examined executive functions as moderators of the relation between self-control and health behaviors (Hofmann et al., 2009a; Pfeffer & Strobach, 2017), with mitigated results. Hence, we currently aimed at addressing the rarely explored approach of executive functions as direct predictor of self-control. As far as we know, only Saunders et al. (2018) and Necka et al. (2018) have investigated the association between executive functions and self-control. Saunders et al. (2018) found no evidence of a correlation between trait selfcontrol and inhibition. Using structural equation modeling, Necka et al. (2018) found no significant association between a "trait self-control" latent variable and an "executive functions" latent variable. However, methodological improvement would allow some resultsrelated pitfalls to be avoided. First, only the relations between latent variables were tested, without examining the independent contribution of each executive function to trait self-control. Second, these previous studies never focused on self-control resources, which are correlated with trait self-control but remain an independent dimension to be considered (Forestier et al., 2018). Third, the possibility that trait self-control and executive functions are associated with health behaviors was not investigated. Yet, the relation between executive functions and health behaviors deserves attention. Indeed, another study showed that individuals with the highest inhibition adopted a less unhealthy diet (Hofmann et al., 2009). Similarly, high updating abilities have been associated with more physical activity (Lambourne, 2006; Pfeffer & Strobach, 2017). Finally, a bi-directional relationship between executive functions and health behavior has been proposed, with individuals with high executive abilities being more likely to

adopt a healthy lifestyle that would, in turn, enhance their executive functions in the long run (Allan et al., 2016). Empirical data has recently been reported supporting this relation (Cheval et al., 2020). Accordingly, if executive functions are correlated with self-control, as advanced theoretically (Hofmann et al., 2012), they could promote health behaviors through direct and indirect effects, partially mediated by trait self-control and self-control resources. Such assumptions have never yet been tested.

The current study aimed to investigate the independent contribution of each executive function to self-control and four crucial health behaviors to prevent noncommunicable diseases, while considering differences among individuals in their trait self-control and self-control resources. For these purposes, structural equation models were used, one for physical activity versus sedentary activity, and a second for a healthy versus an unhealthy diet, as in Forestier et al., (2018). In line with theoretical discussions (Hofmann et al., 2012), we hypothesized that executive functions would positively predict trait self-control and self-control resources (H1) and healthy behaviors (physical activity and healthy diet) (H2), and negatively predict unhealthy behaviors (sedentary activity and unhealthy diet) (H3). Similarly, we hypothesized that trait and self-control resources would positively predict healthy behaviors (H4) and negatively predict unhealthy behaviors (H5). Finally, the mediated relation implies that (H6) executive functions will be positively related to trait self-control and self-control resources, which will in turn be related to health behaviors¹. Figure 1 summarizes our hypotheses.

2. Method

Overview

Participants were recruited via social media, personal mailing lists, and direct advertising messages during classes. They were all students at sports and psychology faculties of three different universities. Data were collected over three weeks (November 2021) by completion of three cognitive tasks and four questionnaires on Inquisit web version 6.3.2.0 (Computer software) (data hosted by Inquisit, repository) (during a single session lasting 1h15). All procedures in this study complied with APA ethical principles. Informed consent was obtained from all participants before the beginning of the study. It should also be noted that the participants were informed that the online study was anonymous and confidential: only a self-generated code allowed their identification.

¹No differential hypotheses regarding the role of trait self-control and self-control resources were formulated because of the rare existing evidences about relations between self-control resources and health behaviors. Moreover, we did not formulate differential hypotheses regarding the role of self-control and behaviors, because (a) despite differences, health behaviors considered share similarities (e.g., long-term benefits), as well as unhealthy behaviors share some (e.g., appetitive) (McEachan et al., 2010); and (b) literature stressed that self-control behave in comparable manner on different healthy (e.g., positive relation) and unhealthy behaviors (e.g., negative relation) (de Ridder et al., 2012).



Figure 1. Hypothetical Models.

Note. These are summarized hypothetical models. The full model will test the relations between each executive function, trait and state self-control and each behavior. RT = Reaction Time, SSRT = Stop-Signal Reaction Time, MVPA = Moderate to Vigorous Physical Activity. Variables with a bold line are latent. Variables with normal line are observed. H6 is the hypothesis related to the effects of executive functions on health behaviors mediated by self-control and is not illustrated.

Participants and sample size

Three procedures were used for estimating our sample size, and its relevance. The first procedure aims to estimate a minimal sample size to reach. The second one aims to determine a stopping rule to fix when data collection will end. The last one aims to compare the sample size reached and the smallest detectable effect size with a certain power to what the literature identified in past studies with common features, to consider whether another phase of data collection is necessary or not. Precisely, first, we used a method specific to structural equation modeling (MacCallum et al., 1996, 2006a; MacCallum & Hong, 1997) to estimate an a priori minimum sample size to obtain a fit index, namely RMSEA, within a given range [0.00; 0.08] (as recommended on the literature, Brown, 2015), with 90% power and $\alpha = .05$. Based on simulations, the minimum sample size was N = 26 (data and code for this estimation are available https://osf.io/hpsjw/?view_only=6e28c8307294494e9eec45d2670efd8d) at (MacCallum et al., 2006b). Second, we estimated an a priori maximum sample size by using the stopping rule based on resource constraints. Because we endorsed no priors regarding an expected effect size, we decided to recruit as many participants as possible during the running of the online study. During these three weeks, 535 people logged on. Exclusion criteria were individuals who: (1) did not consent to participate; (2) completed the study multiple times; (3) responded incorrectly to seriousness checks (Aust et al., 2013); (4) did not consider regular physical activity and healthy diet as important for them (i.e., below 2 on a 1-7 goal-importance scale, Fishbach et al., 2003). In addition, we used the *performance* package (version 0.10.0) (Lüdecke et al., 2021) for R-Studio (R Core Team, 2021) to identify observations that were influential on the nine variables of interest (see Measures section). Specifically, based on a composite score obtained via the application of multiple outlier detection algorithms (Lüdecke et al., 2021), we excluded participants classified as influential by at least half of the methods used by this package (the data and code of this data cleaning are available at https://osf.io/hpsjw/?view_only=6e28c8307294494e9eec45d2670efd8d). The application of these exclusion criteria in the described order led to a final sample size of N = 385 participants (154 women; $M_{age} = 19.42$, $SD_{age} = 2.71$).

Finally, we conducted a sensitivity power analysis with G*Power 3.1.9.4 (Faul et al., 2007) to estimate the minimal effect size on the most constrained multiple regression of the structural equation models. With our convenience sample of N = 385, $n_{predictors} = 5$ (see Measures), power = .90, $\alpha = .05$, the smallest detectable effect size was $f^2 = .04$. This is one of the smallest small-to-medium effect sizes (range = .02 to .15), in line with findings on the relationships between self-control and health behaviors (Pfeffer & Strobach, 2018).

Measures

Independent Variables

Inhibition

A recent consensual stop-signal task² (Verbruggen et al., 2019) was used to assess inhibition. The task included 216 trials in total, splitted in 3 blocks of 72 trials. A typical trial started with a central fixation circle presented for 250 ms, followed by display of the stimulus (a right- or left-pointing white arrow within a circle) until the participant's response. The instruction was to respond systematically according to the direction indicated by the arrow by pressing a predefined keyboard button. However, participants had to stop their response (i.e., not press the key) if a signal beep was made after the presentation of the arrow. The delay between the arrow's presentation and the beep was adjusted up or down by 50 ms as a function of the participant's performance, starting with an initial delay of 250 ms. The delay could be increased up to 1150 ms if the previous signal-stop was successful, and decreased down to 50 ms if the previous signal stop failed. This delay is referred to as the Stop-Signal Reaction Time (SSRT) and gives an estimation for response-inhibition latency in milliseconds. We calculated the SSRT by using the integration method (Verbruggen et al., 2019). The lower the SSRT, the more difficult it is to stop the go-process, and the higher the SSRT, the easier it is to stop the go-process. Accordingly, a lower (higher) SSRT integration means the participant has stronger (weaker) inhibition.

²We preferred the stop-signal task for inhibition because it has been proposed as more closely related to selfcontrol, as it captures more specifically behavioral control, compare to other task such as the Stroop task (supposedly more associated with cognitive inhibition) (Diamond, 2013). We preferred the letter-memory task for updating, because it was the most strongly associated with "updating" latent factor on Miyake et al., (2000) and Miyake & Friedman (2012). We preferred the number-letter task for updating, because it has been proposed as one of the more reliable, and as more appropriate for adults than other task (Diamond, 2013).

Updating

We used a letter memory task to measure updating² (Friedman et al., 2008). A series of letters appeared consecutively in the center of the screen for a duration of 2.5 s for each letter. Written instructions asked participants to recall, in forward order, the last three letters after the last letter's disappearance, by selecting the correct letters from a letter matrix provided. They had to click "blank" if they skipped a particular letter. The number of letters per series varied randomly through time (5, 7, or 9 letters). In total, 12 measurement trials were completed (four of each length). Answers were scored as correct even if the three letters were not recalled in the correct order (Miyake et al., 2000). The more participants were able to recall letters per trial, the better their updating was considered.

Switching

Switching was assessed with a number-letter task² (Miyake et al., 2000). This task involves two categorization tasks, in which character pairs including a letter and a number (e.g., 3T, 4A) were presented. The participants were asked to categorize the pair depending on whether the letter was a consonant or vowel (i.e., letter task), or depending on whether the number was odd or even (i.e., number task). The tasks alternated between categorizing rules in a clockwise fashion, and thus used predictable location cues in a 2x2 matrix (i.e., the top of the matrix for letter categorization and bottom of the matrix for number categorization). Oddnumbered trials were set as "switch task" trials and even-numbered trials as "non-switch task" trials. Participants responded by button press, and the next stimulus was presented 150 ms after the response. The whole task was composed of 128 trials. The reaction time switch cost was calculated by assessing the difference between the correct latency of switch trials and nonswitch trials (Miyake et al., 2000). A positive reaction time switch cost indicates a slower response in switch trials, than in non-switch trials, and conversely. For example, a highly positive reaction time switch cost indicates low switching. Trials with reaction times under 150 ms and above 2000 ms were excluded from analyses (Rossell & Nobre, 2004; Schoonbaert et al., 2011).

Mediating Variables

Trait Self-Control

Trait self-control was assessed with the 13-item version of the Brief Self-Control Scale (Tangney et al., 2004). Participants responded to the following instruction: "For each sentence, choose what suits you best", on a 7-point Likert scale from 1 (*Don't agree at all*) to 7 (*Completely agree*), with regard to the different items ($\alpha = .80$, $\omega = .83$).

Self-Control Resources

Self-control resources were assessed by the subjective vitality scale, as in previous studies (Forestier et al., 2018). Participants were asked to answer the 5-item questionnaire (e.g., "At the moment, I feel alive and full of vitality"), with the following instruction: "For each item, please indicate the general feeling you have experienced over the past 7 days, by selecting the most appropriate number" on a 7-point Likert scale from 1 (*Don't agree at all*) to 7 (*Completely agree*) ($\alpha = .89$, $\omega = .92$).

Dependent Variables

Physical Activity and Sedentary Activity

Physical activity and sedentary activity were measured using the International Physical Activity Questionnaire (Craig et al., 2003). Participants were asked to indicate how much time they had spent doing moderate-intensity and vigorous-intensity physical activities (i.e., MVPA), how much time they had spent walking, and how much time they had spent sitting and/or lying down (i.e., sedentary activity) in minutes, in their daily life over the last 7 days.

Healthy and Unhealthy Diet

Healthy and unhealthy diets were assessed using the Healthy Eating Behavior Scale (Pelletier et al., 2004), composed of two subscales: four items related to a healthy diet (e.g., "I eat fruit and vegetables") and the remaining items related to an unhealthy diet (e.g., "I use white sugar"). Participants indicated their consumption frequency on a 7-item scale ranging from 1 (*once or twice per month*) to 7 (*more than three times per day*).

3. Results

Descriptive statistics and Pearson's correlation coefficients are provided in the Supplementary Materials (Tables S1 and S2). Correlations' table revealed that self-control resources are significantly correlated with trait self-control (r = .21), MVPA (r = .27), sedentary time (r = .14), healthy diet (r = .15), unhealthy diet (r = .12) and switching (r = .13). It also stresses that trait self-control is only significantly correlated with healthy and unhealthy diet (r = .21) and r = .27, respectively). The only behaviors significantly correlated are MVPA and healthy diet (r = .25). Among executive functions scores, switching is significantly corelated with MVPA (r = .10), and inhibition with healthy diet (r = .10).

Structural Equation Modelling

Analytical Strategy

The hypotheses were tested using structural equation modeling with the Lavaan package (version 0.6-8, Rosseel, 2012) in R-Studio (RStudio Team, 2015) (the R script, raw data, and analysis dataset can be found in the Open Science Framework, at https://osf.io/hpsjw/?view only=6e28c8307294494e9eec45d2670efd8d). We used a two-step approach (Anderson & Gerbing, 1988). The first step is a confirmatory factor analysis (CFA). Hence, we verified the construct validity of the measurement model to estimate a reliable one, by examining factor loadings, modification indices and model fit indices. Second, after a satisfactory fit was achieved for the measurement model, we tested the structural model (i.e., the hypothesized relationships between the variables). The results section presents only the structural models (see Measurement Models in Supplementary Materials). Model fit was assessed by examining the comparative fit index (CFI), Tucker-Lewis Index (TLI), and rootmean-square error of approximation (RMSEA), with a satisfactory model having a CFI and a TLI over 0.90, a RMSEA below 0.05 (Brown, 2015). Finally, after an estimation of the full hypothetical model, non-significant paths were removed to estimate model's parsimony reliability (MacCallum & Austin, 2000). The statistical significance was set at $\alpha = .05$. Data were standardized prior to model estimation. Indirect effects (i.e., mediation) were estimated if independent variables and mediators were significantly associated with the dependent variables, with the *RMediation* package (version 1.2.0) (Tofighi & MacKinnon, 2011).

Physical Activity and Sedentary Activity Structural Model

The physical activity and sedentary activity structural model contained two latent variables (trait self-control and self-control resources) and five observed variables (inhibition score, updating score, switching score, MVPA score, and sedentary activity). Moreover, compared with the measurement model, we added covariances between the three executive function scores. The full structural equation model yielded good model-fit indices (χ^2 (130) = 153.43, RMSEA = 0.02, 90% CI [0.00, 0.03], CFI = 0.99, TLI = 0.99). Partially confirming our hypothesis (H1), only one of the three executive function scores considered was significantly associated with self-control. Precisely, switching was negatively related to self-control resources ($\beta = -.10$, 95% CI [-.18, -.01], p = .02, $R^2 = .02$), evidencing that the higher the cost, the lower the self-control resources. Contrary to our hypotheses (H2, and H3), executive function scores were not significantly associated with physical activity and sedentary activity (i.e., no direct effect). In partial accordance with H4 and H5, only self-control resources positively predicted MVPA ($\beta = .31, 95\%$ CI [.18, .43], p<.001, $R^2 = .08$) and negatively predicted sedentary activity ($\beta = -.17, 95\%$ CI [-.30, -.05], $p = .01, R^2 = .03$). Trait self-control was not significantly associated with healthy or unhealthy behaviors. Mediation analysis revealed a significant indirect effect of switching on physical activity (indirect = -.03, 95% CI [-.06, -.00], p = .02) and sedentary activity (*indirect* = .02, 95% CI [.00, .04], p = .03), suggesting total mediations through self-control resources, which partially confirm our hypothesis (H6). Figure 2 shows this structural model³.

Healthy and Unhealthy Diet Structural Model

The healthy and unhealthy diet structural model contained four latent variables (trait selfcontrol and self-control resources, and healthy and unhealthy diet scores), three observed variables (i.e., inhibition, updating, and switching scores), and the covariances between the three executive function scores. The full structural equation model yielded good model-fit indices (χ^2 (188) = 218.35, RMSEA = 0.02, 90% CI [0.00, 0.03], CFI = 0.99, TLI = 0.99). Switching was still associated with self-control resources, as in the physical and sedentary activity model. Contrary to H2, and H3, there was no significant direct association between executive functions with healthy and unhealthy diets. Mostly according with H4 and H5, results revealed that trait self-control positively predicted healthy diet (β = .28, 95% CI [.07, .50], p = .01, R^2 = .10) and negatively predicted unhealthy diet (β = -.64, 95% CI [-.91, -.36], p <.001, R^2 = .19), and that self-control resources also positively predicted healthy diet (β = .13, 95% CI [.02, .23], p = .02, R^2 = .10). Mediation analysis revealed a significant indirect effect of switching on healthy diet (*indirect* = -.01, 95% CI [-.03, -.00], p = .02), suggesting a total

³For exploratory purpose, we conducted the model separately on vigorous and moderate physical activity, and on walking. Tables of these models are in Supplementary Materials (S5, S6, S7)



Figure 2. Physical Activity and Sedentary Activity Full Structural Model

Note. p<0.05, p<0.01, p<0.01, p<0.01. SSRT = Stop-Signal Reaction Time, RT = Reaction Time, BSCS = Brief Self-Control Scale, SV = Subjective Vitality, MVPA = Moderate to Vigorous Physical Activity. Path darkness level distinguishes significant and non-significant relations.

mediation through self-control resources. This partially confirms H6. Figure 3 shows this structural model. Table 1 summarizes regression coefficients of the two structural models (the complete tables are available in the Supplementary Materials, Tables S3 and S4).

4. Discussion

The present study tested the role of executive functions as predictors of individual differences in trait self-control and self-control resources, which are likely also associated with health behaviors (physical activity, healthy diet, sedentary activity, and unhealthy diet). Partially contrary to our hypotheses, we found small evidence supporting the role of executive functions as predictors of individual differences in trait self-control or self-control resources. Precisely, switching was only associated with self-control resources. Similarly, no direct role of these functions regarding healthy and unhealthy behaviors was observed. Nevertheless, in support of our hypotheses, there was an association between individual differences in selfcontrol and health behaviors. Individuals with higher self-control resources practiced more physical activity, ate healthier, and spent less time being sedentary than individuals with lower self-control resources. It also indicated that individuals with higher trait self-control adopted a healthier diet, and a less unhealthy one, than individuals with lower trait self-control. These findings stress the central role of self-control, and especially of self-control resources, for adopting health behaviors. Finally, we observed three indirect effects of switching on behaviors, totally mediated by self-control resources. Individuals with higher switching were more physically active, less sedentary, and ate healthier. through higher self-



Figure 3. Healthy and Unhealthy Diet Full Structural Model.

Note. p<0.05, p<0.01, p<0.01, p<0.001. SSRT = Stop-Signal Reaction Time, RT = Reaction Time, BSCS = Brief Self-Control Scale, SV = Subjective Vitality, HBES = Healthy Eating Behavior Scale. Path darkness level distinguishes significant and non-significant relations.

control resources. These findings pave the way to a more refined understanding of the predictors of individual differences in self-control resources, and to the ways by which executive functioning could influence health behaviors.

Relations Between Executive Functions, Self-Control, and Health Behaviors

Partially according with Necka et al. (2018) and Saunders et al. (2018), our study did not find strong evidence of significant associations between executive functions and selfcontrol. However, our intention was to examine the contribution of each executive function to self-control and health behaviors. Indeed, it was proposed that updating and inhibition might be the most important executive functions for self-control, enabling a better representation of the goal and a better inhibition for fighting a threatening temptation (Hofmann et al., 2012). However, our study does not support these suggestions.

Suggestions were divided concerning the role of switching. On the one hand, , when facing a motivational conflict, individuals with high switching could efficiently switch from an ineffective conflict resolution strategy (e.g., resisting temptation) to a situationally more effective (e.g., avoiding temptation) (Hofmann et al., 2012). On the other hand, individuals with high switching could present lower self-control as this switching could promote quick and efficient disengagement from a goal-oriented mindset to a mindset oriented toward the pursuit of tempting alternatives (Hofmann et al., 2012). Our results support partially the first statement. Individuals with high switching are more likely to be able to shift their mind toward subjective feelings permitting goal-attainment strategies, such as high self-control resources, useful for efficient self-control act and adaptative motivational-conflict resolution.

	Physical Activity and	l Sedentary	Time Model				
Independent variable	Dependent variable	Estimate	Estimate 95%CI [LL, UL]	Std. Err.	Z	р	R^2
	Regres	sion Slopes					
SSRT integration (I)		0.02	[-0.06, 0.11]	0.04	0.58	.562	
Mean correct letters (U)	Self-control resources	0.02	[-0.06, 0.10]	0.04	0.47	.638	.015
RT switch cost (S)		-0.10*	[-0.18, -0.01]	0.04	-2.27	.023	
SSRT integration (I)		-0.02	[-0.06, 0.03]	0.03	-0.61	.541	
Mean correct letters (U)	Trait self-control	0.00	[-0.04, 0.05]	0.02	0.18	.860	.001
RT switch cost (S)		0.00	[-0.04, 0.05]	0.02	0.20	.842	
SSRT integration (I)		0.04	[-0.06, 0.14]	0.05	0.81	.418	
Mean correct letters (U)		0.00	[-0.09, 0.10]	0.05	0.10	.924	
RT switch cost (S)	MVPA	-0.07	[-0.17, 0.03]	0.05	-1.44	.150	.081
Self-control resources		0.31***	[0.18, 0.43]	0.06	4.83	.000	
Trait self-control		0.06	[-0.18, 0.30]	0.12	0.51	.609	
SSRT integration (I)		-0.06	[-0.16, 0.04]	0.05	-1.11	.266	
Mean correct letters (U)		-0.01	[-0.11, 0.09]	0.05	-0.27	.790	.029
RT switch cost (S)	Sedentary activity	0.04	[-0.06, 0.14]	0.05	0.77	.441	
Self-control resources		-0.17**	[-0.30, -0.05]	0.06	-2.71	.007	
Trait self-control		-0.02	[-0.27, 0.23]	0.13	-0.16	.874	
	Fit	Indices					
χ^2		153.43					
χ^2_df		130.00					
p_{χ^2}		.079					
CFI		.99					
TLI		.99					
RMSEA		.02	[0.00, 0.03]				
	Healthy and Un	healthy Die	et Model				
	Regress	sion Slopes					
SSRT integration (I)		0.03	[-0.06, 0.11]	0.04	0.58	.559	_

Table 1. Regression Coefficients from Structural Equation Models.

Mean correct letters (U)	Self-control resources	0.02	[-0.06, 0.11]	0.04	0.49	.627	.016
RT switch cost (S)		-0.10*	[-0.18, -0.01]	0.04	-2.28	.023	
SSRT integration (I)	Trait self-control	-0.02	[-0.07, 0.03]	0.03	-0.61	.542	.002

Mean correct letters (U)		0.00	[-0.05, 0.05]	0.03	0.18	.856	
RT switch cost (S)		0.01	[-0.04, 0.06]	0.03	0.24	.813	
SSRT integration (I)		-0.07	[-0.16, 0.01]	0.04	-1.76	.078	
Mean correct letters (U)		0.07	[-0.01, 0.16]	0.04	1.73	.084	
RT switch cost (S)	Healthy diet	0.06	[-0.02, 0.14]	0.04	1.41	.159	.097
Self-control resources		0.13*	[0.02, 0.23]	0.05	2.34	.019	
Trait self-control		0.28**	[0.07, 0.50]	0.11	2.62	.009	
SSRT integration (I)		0.02	[-0.07, 0.12]	0.05	0.47	.637	
Mean correct letters (U)		-0.02	[-0.11, 0.08]	0.05	-0.33	.743	
RT switch cost (S)	Unhealthy diet	-0.07	[-0.16, 0.03]	0.05	-1.36	.174	.194
Self-control resources		-0.09	[-0.21, 0.02]	0.06	-1.55	.121	
Trait self-control		-0.64***	[-0.91, -0.36]	0.14	-4.56	.000	
		Fit Indices					
χ^2		218.35					
χ^2_df		188.00					
p_{χ^2}		0.06					
CFI		0.99					
TLI		0.98					
RMSEA		0.02	[0.00, 0.03]				

Note. *p<0.05, **p<0.01, ***p<0.001. MVPA = Moderate to vigorous physical activity, SSRT = Stop-Signal Reaction Time, I = Inhibition, U = Updating, S = Switching

Our findings also support the absence of evidence in favor of direct relations between executive functions, trait self-control and physical activity, as observed in some previous studies. Pfeffer and Strobach (2017) showed that most composite executive functions scores they calculated were not significantly correlated with trait self-control, except for two switching scores that were, modestly (i.e., task-cueing $R^2 = .04$, alternating-runs $R^2 = .03$; Pfeffer & Strobach, 2017). They also revealed that most executive function scores were not significant direct predictors of intention-behavior gap, except for updating score. These findings highlighted no direct relations either between executive functions and trait self-control or between executive functions and a physical activity, which is consistent with the current results. Interestingly, Pfeffer et Strobach (2017) found that half of the executive-function scores they considered (one inhibition, one updating, and one switching score) moderated the effects of trait self-control on the physical activity intention-behavior gap. Together with our results, this suggests that updating and inhibition are not direct predictors of individual differences in selfcontrol and physical activity, but could rather moderate the relation between self-control and this behavior. However, because the other half of the executive-function scores they considered (one inhibition score, one updating score, and one switching score) showed no interaction with self-control to predict physical activity, further investigations are required.

Similarly, the fact that we found no significant direct relations between executive functions and unhealthy diet were consistent with Hofmann et al. (2009). Indeed, there study stressed no direct correlation between candy consumption and different components of inhibition, but these latest (i.e., executive attention, behavioral inhibition, affect regulation) consistently moderated the relations between automatic affective reactions and candy consumption. All other things being equal, our study and the aforementioned results (Hofmann et al., 2009; Necka et al., 2018; Pfeffer & Strobach, 2017) taken together suggest that inhibition and updating are not direct predictors of self-control or healthy or unhealthy behaviors, but could moderate relations between affective reactions (e.g., automatic affective reactions, conscious experience of temptations) and behaviors, and between self-control and health behaviors. Investigations of inhibition and updating as moderators of the relation between self-control and health behaviors would be of particular interest.

Relations Between Self-Control and Health Behaviors

All the relations found between self-control and health behaviors are consistent with the literature (de Ridder et al., 2011, 2012; Forestier et al., 2018). Specifically, self-control resources were related to physical activity, sedentary activity, and healthy diet, while trait selfcontrol was significantly related only to healthy and unhealthy diet. Furthermore, self-control aspects have different effects depending on the behavior examined, with quite a similar effect size previously estimated (Forestier et al., 2018). Precisely, self-control resources were related to health behaviors with a descriptively comparable effect size (i.e., $R^2 = .08$ for physical activity, and $R^2 = .10$ for healthy diet) and a smaller effect size for the unhealthy behavior (R^2 = .03). It suggests that self-control resources are likely efficient to promote health behaviors, but less effective in preventing the unhealthy ones. Health behaviors show differences as well as similarities. For example, physical activity, and a healthy diet are comparable as they require to be initiated, while sedentary activity and an unhealthy diet are both things that need to be stopped (McEachan et al., 2010). Nevertheless, physical activity requires more effort to be initiated than a healthy diet (McEachan et al., 2010), and sedentary activities appear to be attractive because they preserve energy expenditure (Cheval & Boisgontier, 2021), while unhealthy food seems attractive because of the immediate pleasure it provides (Appelhans, 2009; Volkow et al., 2011). Another interesting perspective could be to investigate the influence of behavioral features on self-control aspects that could be effective or ineffective in the conflict resolution. This encouraging finding requires further investigations, for example with other studies' design (see "Strengths, Limitations, and Future Work Perspectives"), or with other instruments to capture the behaviors, such as accelerometers for physical and sedentary activities, and daily diet diary or questionnaires such as the new Healthy and Unhealthy Eating Behavior Scale (Guertin et al., 2020) for diet behavior, to confirm the crucial role of self-control resources for health behaviors.

Strengths, Limitations, and Future Work Perspectives

Several limitations of the present study need to be addressed. First, our study sample consisted of young and relatively healthy students. Psychological determinants driving behavior maintenance could differ from those driving behavior change (e.g., habit vs. coping

planning). Hence the current results need to be replicated in individuals engaged in health behavior change processes. Second, the cross-section of the current study is insufficient to understand the role of within-person variations in executive functions and self-control in daily fluctuations of health behaviors. Nevertheless, the within-person variations of inhibition seem more predictive of snack consumption (i.e., unhealthy diet) than individual differences in inhibition (Powell et al., 2017). In addition, an important part of the variance of self-control resources is found at the within-person level (i.e., 60%) despite variance at the between-person level (Smolders et al., 2013). Thus, longitudinal study designs with daily repeated measures will be required to properly examine the relationships of within-person executive functions and self-control resource variations with health behavior fluctuations. Third, our study considered executive functions and self-control as predictors of the overall level of health behaviors over a week, without measuring the participant's intention to engage in these behaviors. Despite including only individuals who considered physical activity and healthy diet important for them, it remains possible that they did not support a particular intention to engage in healthy behaviors during the week we considered. For example, some participants may not have practiced physical activity because they did not intend to, rather than because of low selfcontrol. Future studies could assess intention-behavior gap instead of health behaviors' global level over a week. In line with previous studies (Pfeffer et al., 2020; Pfeffer & Strobach, 2017), participants could be asked their intention to engage in a certain quantity of physical activity, to avoid a certain quantity of sedentary activity, to adopt a healthy diet, and to avoid unhealthy food before and after all the measurements. Then the discrepancy between intention endorsed and behaviors actually adopted (i.e., intention-behavior gap) could be assessed to examine the role of executive functions and self-control in reducing this gap. Finally, the self-reported nature of the self-control and behaviors measures is probably another limitation of our study. As significant associations were observed between certain self-reported measures (e.g., selfcontrol resources and physical activity), we cannot exclude that a part of these associations was because of a common method bias. However, we also observed association between reactiontime task and self-reported measures (e.g., updating and self-control resources), and also evidenced absence of significant association between other self-reported measures (e.g., trait self-control and behaviors). Though, these specific associations could rather suggest meaningful associations rather a method artifact. Altogether, direct and conceptual (e.g., different measures and sample) replications could provide valuable information, and identify the robustness of current (un)significant relations.

This study, nevertheless, has several strengths. We first examined the relative and distinct role of the three executive functions, namely inhibition, updating, and switching, by using executive tasks according to recent literature (e.g., Verbruggen et al., 2019). We also tested our hypotheses with structural equation modeling, which increases the reliability of scores and relations by (a) explicitly assessing the measurement error; (b) estimating latent variable scores by scoring observed variables rather than other aggregating methods; and (c) testing a model where a structure (e.g., covariances) could be imposed and assessed as to fit of the data (Novikova et al., 2013). The final strength of our study is its good power to detect small effect size (i.e., power = .90 for $f^2 = .04$).

Conclusion

No evidence was found supporting executive functions as direct predictors of the four health behaviors considered. However, the current results support the role of self-control resources as a potential way to promote physical activity and reduce sedentary activity, and trait self-control as a likely determinant to increase adoption of a healthy diet and lower that of an unhealthy diet. In sum, we hypothesize that *cold* executive functions may not explain individual differences in self-control or health behaviors, and that the aspects of self-control (trait or state) that are effective in health behavior adoption depend on the behavioral domain. This study paves the way to longitudinal studies at the within-person level assessing the effects of *hot* "affective-related" executive functions on trait and self-control resources and health behaviors. Those effects can be tested by using affectively-charged executive function in which the neutral stimuli (e.g., arrows, letter or number) are replaced by affective stimuli such as pictograms of physical or sedentary activity, or of healthy of unhealthy food (e.g., see Forestier et al., 2022b, p. 27-28, for a discussion). They can also be tested by using self-control measures specific to the behaviors considered (e.g., self-control resources for resolving physical-activity related motivational conflict).

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Supplementary Materials

	Self-control resources	Trait self-control	MVPA (min/week)	Sedentary activity (min/week)	Healthy diet	Unhealthy diet	SSRT Integration (I, ms)	Mean correct letters (U)	Reaction time switch cost (S, ms)
Mean	4.28	4.44	308.14	1970.49	5.20	2.76	237.64	2.86	362.58
Median	4.40	4.38	260.00	1800.00	5.25	2.75	235.67	2.92	351.99
SD	1.26	0.88	211.62	1335.39	0.92	0.95	79.50	0.22	128.25
Min	1.00	1.46	0.00	40.00	2.00	1.00	24.44	0.67	30.35
Max	7.00	6.92	940.00	6300.00	7.00	6.00	493.11	3.00	693.44
Cronbach Alpha	0.89	0.80	-	-	0.48	-0.25	-	-	-
McDonalds Omega	0.92	0.83	-	-	0.52	0.26	-	-	-
Skeweness	-0.27	0.04	0.80	0.63	-0.47	0.52	0.45	-3.91	0.19
Kurtosis	2.79	2.78	2.90	2.79	2.71	3.34	3.64	29.16	2.82

Table S1. Descriptive statistics

Note. MVPA = Moderate to Vigorous Physical Activity, SSRT = Stop-Signal Reaction Time, I = Inhibition, U = Updating, S = Switching, min = minutes, ms = milliseconds

Variable	1	2	3	4	5	6	7	8
1. Self-control resources								
2. Trait self- control	.21** [.11, .30]							
3. MVPA	.27** [.17, .36]	.04 [06, .14]						
4. Sedentary activity	14** [24,04]	00 [10, .10]	06 [15, .05]					
5. Healthy diet	.15** [.05, .25]	.21** [.11, .30]	.25** [.15, .34]	.04 [06, .14]				
6. Unhealthy diet	12* [21,02]	27** [36,18]	.02 [08, .12]	02 [12, .08]	.00 [10, .10]			
7. SSRT Integration (I)	.03 [07, .13]	04 [14, .06]	.05 [05, .15]	06 [16, .04]	10* [20,00]	04 [14, .06]		
8. Mean correct letters (U)	.03 [07, .13]	.02 [08, .12]	.01 [09, .11]	01 [11, .09]	.09 [01, .19]	.02 [08, .12]	07 [17, .03]	
9. Reaction time switch cost (S)	13* [23,03]	.04 [06, .14]	10* [20,00]	.06 [04, .16]	.07 [03, .17]	03 [13, .07]	06 [16, .04]	.03 [07, .13]

 Table S2. Correlations with confidence intervals

Note. Values in square brackets indicate the 95% confidence interval, a plausible range of population correlations that could have caused the sample correlation (Cumming, 2014). * indicates p < .05, ** indicates p < .01. MVPA = Moderate to Vigorous Physical Activity, SSRT = Stop-Signal Reaction Time, I = Inhibition, U = Updating, S = Switching, min = minutes, ms = milliseconds

Physical Activity and Sedentary Activity Measurement Model

The first physical activity and sedentary activity CFA included two latent variables (trait self-control and self-control resources). The latent variable "trait self-control" was specified with the 13 items of the brief self-control scale; the latent variable "self-control resources" was specified with the five items of the subjective vitality scale. Results showed satisfactory loadings to the latent variables, except for three items from the Brief Self-Control Scale (i.e., items 1, 6 and 11), with loadings below .40 being removed (Hair et al., 2013). According to modification indices, theoretically meaningful covariances between variables were added to improve the model fit (Whittaker, 2012). Precisely, we only included covariances between items from the same scale and stopped when an additional covariance did not improve model fit to keep the most parsimonious model. Measurement model with covariances showed good model-fit indices (χ^2 (130) = 153.43, RMSEA = 0.02, 90% CI [0.00, 0.03], CFI = 0.99, TLI = 0.99).

Healthy And Unhealthy Diet Measurement Model

The first healthy and unhealthy diet CFA included four latent variables (trait selfcontrol, self-control resources, healthy diet score, and unhealthy diet score). The latent variable representing trait self-control and self-control resources was specified with the same items as for the previous CFA (i.e., 10 items for trait self-control, 5 items for self-control resources). The latent variable representing healthy and unhealthy diet was respectively specified with the four items of the Healthy Eating Behavior Scale (HEBS) representing healthy food consumption, and the four items representing unhealthy food consumption. Results showed satisfactory loadings to the latent variables, except for one item from the HEBS, healthy diet dimension (item 4), and two items from the HEBS, unhealthy diet dimension (items 3 and 4), with loadings below .40 being removed (Hair et al., 2013). Compared with the physical activity and sedentary activity CFA, modification indices did not suggest new additional important covariances to consider. The measurement model with covariances showed good model-fit indices (χ^2 (188) = 218.35, RMSEA = 0.02, 90% CI [0.00, 0.03], CFI = 0.99, TLI = 0.98).

Independent variable	Dependent variable	Estimate	Estimate 95%CI [LL, UL]	Std. Err.	Z	р	R^2
	Factor	Loadings					
SV.1		1.00^{+}	[1.00, 1.00]				
SV.2		1.04***	[0.98, 1.11]	0.03	31.84	.000	
SV.3	Self-control resources	0.52***	[0.39, 0.64]	0.06	8.28	.000	
SV.4		1.10***	[0.96, 1.24]	0.07	15.17	.000	
SV.5		1.15***	[1.01, 1.30]	0.07	15.40	.000	
BSCS.2		1.00^{+}	[1.00, 1.00]				
BSCS.3		1.35***	[0.91, 1.79]	0.22	6.05	.000	
BSCS.4		0.85***	[0.56, 1.14]	0.15	5.68	.000	
BSCS.5		0.80***	[0.49, 1.12]	0.16	5.03	.000	
BSCS.7	TT : 4 10 4 1	1.31***	[0.93, 1.69]	0.19	6.78	.000	
BSCS.8	I rait self-control	1.43***	[0.95, 1.90]	0.24	5.90	.000	
BSCS.9		1.20***	[0.79, 1.60]	0.21	5.83	.000	
BSCS.10		1.46***	[1.01, 1.91]	0.23	6.39	.000	
BSCS.12		1.18***	[0.81, 1.55]	0.19	6.26	.000	
BSCS.13		0.92***	[0.61, 1.24]	0.16	5.82	.000	
	Regressi	on Slopes					
SSRT integration (I)		0.02	[-0.06, 0.11]	0.04	0.58	.562	
Mean correct letters (U)	Self-control resources	0.02	[-0.06, 0.10]	0.04	0.47	.638	.015
RT switch cost (S)		-0.10*	[-0.18, -0.01]	0.04	-2.27	.023	
SSRT integration (I)		-0.02	[-0.06, 0.03]	0.03	-0.61	.541	
Mean correct letters (U)	Trait self-control	0.00	[-0.04, 0.05]	0.02	0.18	.860	.001
RT switch cost (S)		0.00	[-0.04, 0.05]	0.02	0.20	.842	
SSRT integration (I)		0.04	[-0.06, 0.14]	0.05	0.81	.418	
Mean correct letters (U)		0.00	[-0.09, 0.10]	0.05	0.10	.924	
RT switch cost (S)	MVPA	-0.07	[-0.17, 0.03]	0.05	-1.44	.150	.081
Self-control resources		0.31***	[0.18, 0.43]	0.06	4.83	.000	
Trait self-control		0.06	[-0.18, 0.30]	0.12	0.51	.609	

Table S3. Physical Activity and Sedentary Activity Full Structural Equation Model

SSRT integration (I)		-0.06	[-0.16, 0.04]	0.05	-1.11	.266	
Mean correct letters (U)		-0.01	[-0.11, 0.09]	0.05	-0.27	.790	
RT switch cost (S)	Sedentary activity	0.04	[-0.06, 0.14]	0.05	0.77	.441	.029
Self-control resources		-0.17**	[-0.30, -0.05]	0.06	-2.71	.007	
Trait self-control		-0.02	[-0.27, 0.23]	0.13	-0.16	.874	
	Residual V	ariances					
SV.1		0.31***		0.04	7.31	.000	
SV.2		0.25***		0.04	5.80	.000	
SV.3		0.81***		0.06	13.50	.000	
SV.4		0.16***		0.05	3.53	.000	
SV.5		0.08		0.05	1.60	.110	
BSCS.2		0.79***		0.06	12.44	.000	
BSCS.3		0.63***		0.07	9.08	.000	
BSCS.4		0.85***		0.06	13.31	.000	
BSCS.5		0.86***		0.07	13.18	.000	
BSCS.7		0.65***		0.06	11.16	.000	
BSCS.8		0.58***		0.08	7.57	.000	
BSCS.9		0.71***		0.07	10.61	.000	
BSCS.10		0.56***		0.07	8.57	.000	
BSCS.12		0.72***		0.07	10.26	.000	
BSCS.13		0.83***		0.06	12.94	.000	
MVPA		0.92***		0.07	13.82	.000	
Sedentary activity		0.97***		0.07	13.85	.000	
SSRT integration (I)		1.00***		0.07	13.86	.000	
Mean correct letters (U)		1.00***		0.07	13.86	.000	
RT switch cost (S)		1.00***		0.07	13.86	.000	
	Residual Co	variances					
BSCS.5	BSCS.9	0.01	[-0.06, 0.09]	0.04	0.36	.720	
SV.1	SV.2	0.15***	[0.07, 0.23]	0.04	3.64	.000	
SV.4	SV.5	-0.07	[-0.16, 0.02]	0.05	-1.43	.151	
BSCS.5	BSCS.12	0.23***	[0.13, 0.32]	0.05	4.74	.000	
BSCS.4	BSCS.5	0.21***	[0.13, 0.30]	0.04	4.81	.000	
BSCS.12	BSCS.13	0.13**	[0.04, 0.23]	0.05	2.80	.005	
BSCS.9	BSCS.10	0.10*	[0.00, 0.20]	0.05	1.96	.050	
BSCS.2	BSCS.8	-0.14**	[-0.22, -0.05]	0.05	-2.98	.003	
BSCS.4	BSCS.13	0.16***	[0.07, 0.24]	0.04	3.50	.000	
BSCS.9	BSCS.13	0.10^{*}	[0.02, 0.18]	0.04	2.43	.015	
BSCS.3	BSCS.9	0.04	[-0.06, 0.14]	0.05	0.74	.462	

BSCS.5	BSCS.8	0.07	[-0.02, 0.15]	0.04	1.48	.138	
BSCS.8	BSCS.9	-0.09	[-0.19, 0.01]	0.05	-1.74	.082	
BSCS.5	SCS.13	0.10*	[0.02, 0.19]	0.05	2.30	.022	
BSCS.7	BSCS.12	-0.10*	[-0.19, -0.02]	0.04	-2.31	.021	
BSCS.2	BSCS.12	0.05	[-0.05, 0.14]	0.05	0.98	.328	
BSCS.8	BSCS.12	-0.13*	[-0.24, -0.03]	0.05	-2.53	.012	
BSCS.3	BSCS.8	-0.01	[-0.12, 0.10]	0.06	-0.15	.878	
BSCS.3	BSCS.12	-0.10*	[-0.19, -0.01]	0.05	-2.24	.025	
BSCS.8	BSCS.10	-0.10	[-0.21, 0.01]	0.06	-1.78	.075	
BSCS.2	BSCS.4	0.06	[-0.02, 0.15]	0.04	1.39	.166	
BSCS.3	BSCS.10	-0.07	[-0.18, 0.03]	0.05	-1.45	.147	
BSCS.2	BSCS.13	0.04	[-0.05, 0.13]	0.05	0.92	.359	
SV.3	SV.5	-0.03	[-0.08, 0.02]	0.03	-1.07	.286	
MVPA	Sedentary activity	-0.01	[-0.10, 0.09]	0.05	-0.19	.848	
SSRT integration (I)	RT switch cost (S)	-0.06	[-0.16, 0.04]	0.05	-1.23	.219	
SSRT integration (I)	Mean correct letters (U)	-0.07	[-0.17, 0.03]	0.05	-1.37	.171	
Mean correct letters (U)	RT switch cost (CSF)	0.03	[-0.07, 0.13]	0.05	0.50	.615	
````````````````````````````````	Latent Va	riances	E · E				
Self-control resources		0.68***		0.08	8.94	.000	0.02
Trait self-control		0.20***		0.05	3.90	.000	0.00
	Latent Cov	variances					
Self-control resources	Trait self-control	0.09***	[0.04, 0.14]	0.02	3.70	.000	
	Fit Inc	lices					
$\chi^2$		153.43					
$\chi^2_df$		130.00					
$p_{\chi^2}$		.079					
p_Baseline		0.00					
GFI		0.96					
AGFI		0.94					
NFI		0.94					
NNFI		0.99					
CFI		0.99					
TLI		0.99					
RMSEA		0.02	[0.00, 0.03]				
p_RMSEA		1.00					
Loglikelihood		-9682.89					
AIC		19525.79					
		19841.84					
BIC							
BIC (adj.)		19588.01					

*Note*. *Fixed parameter *p<0.05, **p<0.01, ***p<0.001. MVPA = Moderate to Vigorous Physical Activity, SSRT = Stop-Signal Reaction Time, I = Inhibition, U = Updating, S = Switching.

Independent variable	Dependent variable	Estimate	Estimate 95%CI [LL, UL]	Std. Err.	Z	р	<i>R</i> ²	-
	Factor	Loadings						_
SV.1		$1.00^{+}$	[1.00, 1.00]					
SV.2		1.04***	[0.98, 1.11]	0.03	31.84	.000		
SV.3	Self-control resources	0.51***	[0.39, 0.64]	0.06	8.21	.000		
SV.4		1.09***	[0.94, 1.25]	0.08	14.08	.000		
SV.5		1.15***	[0.99, 1.30]	0.08	14.18	.000		
BSCS.2		$1.00^{+}$	[1.00, 1.00]					_
BSCS.3		1.31***	[0.91, 1.72]	0.21	6.34	.000		
BSCS.4		0.83***	[0.55, 1.11]	0.14	5.77	.000		
BSCS.5		0.80***	[0.50, 1.10]	0.15	5.20	.000		
BSCS.7	Trait self-control	1.27***	[0.91, 1.63]	0.18	6.95	.000		
BSCS.8		1.39***	[0.95, 1.84]	0.23	6.15	.000		
BSCS.9		1.17***	[0.80, 1.55]	0.19	6.11	.000		
BSCS.10		1.42***	[1.00, 1.83]	0.21	6.69	.000		
BSCS.12		1.16***	[0.81, 1.51]	0.18	6.47	.000		
BSCS.13		0.91***	[0.61, 1.21]	0.15	5.94	.000		
AE 1		1.00+	[1.00, 1.00]	0110				-
AE 2	Healthy diet	0.81***	[0.62, 1.00]	0 10	8 4 2	000		
AF 3	5	0.01	[0.77, 1.21]	0.10	8.75	000		
		1.00+	[0.77, 1.21]	0.11	0.75	.000		
AD.3	Unhealthy diet	0.41**	[1.00, 1.00]	0.16	2.60	000		
AD.4	Regress	0.41 tion Slopes	[0.10, 0.72]	0.10	2.00	.009		-
SSRT integration (I)	108/055	0.03	[-0.06, 0.11]	0.04	0.58	559		-
Mean correct letters (U)	Self-control resources	0.02	[-0.06, 0.11]	0.04	0.49	.627	.016	
RT switch cost (S)		-0.10*	[-0.18, -0.01]	0.04	-2.28	.023		
SSRT integration (I)		-0.02	[-0.07, 0.03]	0.03	-0.61	.542		-
Mean correct letters (U)	Trait self-control	0.00	[-0.05, 0.05]	0.03	0.18	.856	.002	
RT switch cost (S)		0.01	[-0.04, 0.06]	0.03	0.24	.813		_
SSRT integration (I)		-0.07	[-0.16, 0.01]	0.04	-1.76	.078		
Mean correct letters (U)		0.07	[-0.01, 0.16]	0.04	1.73	.084		
RT switch cost (S)	Healthy diet	0.06	[-0.02, 0.14]	0.04	1.41	.159	.097	
Self-control resources		0.13*	[0.02, 0.23]	0.05	2.34	.019		
Trait self-control		0.28**	[0.07, 0.50]	0.11	2.62	.009		_
SSRT integration (I)	Unhealthy diet	0.02	[-0.07, 0.12]	1	0.05	0.47	.637	.19

## Table S4. Healthy and Unhealthy Diet Full Structural Equation Model

Mean correct letters (U)		-0.02	[-0.11, 0.08]	0.05	-0.33 .743	
RT switch cost (S)		-0.07	[-0.16, 0.03]	0.05	-1.36 .174	
Self-control resources		-0.09	[-0.21, 0.02]	0.06	-1.55 .121	
Trait self-control		-0.64***	[-0.91, -0.36]	0.14	-4.56 .000	
	Residue	al Variances				
SV.1		0.31***		0.05	6.58 .000	
SV.2		0.24***		0.05	5.12 .000	
SV.3		0.81***		0.06	13.50 .000	
SV.4		0.17**		0.05	3.28 .001	
SV.5		0.09		0.06	1.55 .122	
BSCS.2		0.78***		0.06	12.42 .000	
BSCS.3		0.63***		0.07	9.47 .000	
BSCS.4		0.85***		0.06	13.34 .000	
BSCS.5		0.86***		0.07	13.16 .000	
BSCS.7		0.66***		0.06	11.54 .000	
BSCS.8		0.58***		0.07	7.99 .000	
BSCS.9		0.70***		0.06	10.84 .000	
BSCS.10		0.57***		0.06	9.10 .000	
BSCS.12		0.71***		0.07	10.52 .000	
BSCS.13		0.82***		0.06	12.97 .000	
HBES.1		0.48***		0.06	7.69 .000	
HBES.2		0.66***		0.06	11.07 .000	
HBES.5		0.50***		0.06	7.91 .000	
HBES.6		0.43*		0.21	2.03 .042	
HBES.8		0.90***		0.07	12.16 .000	
SSRT integration (I)		$1.00^{+}$				
Mean correct letters (U)		$1.00^{+}$				
RT switch cost (S)		$1.00^{+}$				
	Residual	l Covariances				
BSCS.5	BSCS.9	0.01	[-0.06, 0.09]	0.04	0.27 .784	
SV.1	SV.2	0.14**	[0.05, 0.23]	0.05	3.17 .002	
SV.4	SV.5	-0.06	[-0.16, 0.04]	0.05	-1.19 .235	
BSCS.5	BSCS.12	0.22***	[0.13, 0.31]	0.05	4.66 .000	
BSCS.4	BSCS.5	0.21***	[0.12, 0.30]	0.04	4.76 .000	
BSCS.12	BSCS.13	0.13**	[0.04, 0.22]	0.05	2.78 .005	
BSCS.9	BSCS.10	0.10*	[0.01, 0.20]	0.05	2.07 .039	
BSCS.2	BSCS.8	-0.14**	[-0.23, -0.06]	0.04	-3.23 .001	
BSCS.4	BSCS.13	0.15***	[0.07, 0.24]	0.04	3.50 .000	

BSCS.9	BSCS.13	0.10*	[0.02, 0.17]	0.04	2.39	.017	
BSCS.3	BSCS.9	0.04	[-0.06, 0.13]	0.05	0.73	.465	
BSCS.5	BSCS.8	0.06	[-0.03, 0.14]	0.04	1.32	.187	
BSCS.8	BSCS.9	-0.10	[-0.19, 0.00]	0.05	-1.90	.057	
BSCS.5	BSCS.13	0.10*	[0.01, 0.19]	0.05	2.23	.026	
BSCS.7	BSCS.12	-0.10*	[-0.18, -0.01]	0.04	-2.30	.021	
BSCS.2	BSCS.12	0.04	[-0.05, 0.13]	0.05	0.83	.407	
BSCS.8	BSCS.12	-0.14**	[-0.24, -0.04]	0.05	-2.67	.008	
BSCS.3	BSCS.8	-0.01	[-0.11, 0.09]	0.05	-0.17	.863	
BSCS.3	BSCS.12	-0.10*	[-0.19, -0.01]	0.04	-2.28	.023	
BSCS.8	BSCS.10	-0.10	[-0.20, 0.01]	0.05	-1.85	.064	
BSCS.2	BSCS.4	0.06	[-0.03, 0.14]	0.04	1.34	.180	
BSCS.3	BSCS.10	-0.07	[-0.17, 0.02]	0.05	-1.45	.146	
BSCS.2	BSCS.13	0.04	[-0.05, 0.12]	0.04	0.81	.416	
SV.3	SV.5	-0.02	[-0.08, 0.03]	0.03	-0.90	.367	
SSRT integration (I)	Mean correct letters (U)	$-0.07^{+}$	[-0.07, -0.07]				
SSRT integration (I)	RT switch cost (S)	$-0.06^{+}$	[-0.06, -0.06]				
Mean correct letters (U)	RT switch cost (S)	$0.03^{+}$	[0.03, 0.03]				
	Latent	Variances					
Self-control resources		0.68***		0.08	8.71	.000	0.02
Trait self-control		0.21***		0.05	4.05	.000	0.00
	Latent C	Covariances					
Self-control resources	Trait self-control	0.09***	[0.04, 0.14]	0.03	3.72	.000	
Healthy diet	Unhealthy diet	-0.06	[-0.13, 0.02]	0.04	-1.43	.152	
<u>.</u>	Fit	Indices					
$\chi^2$		218.35					
$\chi^2_df$		188.00					
$p_{\chi^2}$		0.06					
p_Baseline		0.00					
GFI		0.95					
AGFI		0.92					
NFI		0.92					
NNFI		0.98					
CFI		0.99					
TLI		0.98					
RMSEA		0.02	[0.00, 0.03]				
p_KMSEA		1.00					
Loglikelihood		-9553.84					
AIC		192/1.69					
BIC		19595.64					
BIC (adj.)		19335.47			_		

*Note*. ⁺Fixed parameter ^{*}p<0.05, ^{**}p<0.01, ^{***}p<0.001. MVPA = Moderate to Vigorous Physical Activity, SSRT = Stop-Signal Reaction Time, I = Inhibition, U = Updating, S = Switching.

Parameter	Coefficient	95% CI	z	р	Component	Fit
SCR =~ vita_1	1.00	[1.00, 1.00]		<.001	Loading	
$SCR = vita_2$	1.04	[0.98, 1.11]	31.84	<.001	Loading	
$SCR = vita_3$	0.52	[0.39, 0.64]	8.31	<.001	Loading	
$SCR = vita_4$	1.09	[0.96, 1.23]	15.57	<.001	Loading	
$SCR = vita_5$	1.15	[1.01, 1.29]	15.90	<.001	Loading	
$TSC = BSCS_2$	1.00	[1.00, 1.00]		<.001	Loading	
$TSC = BSCS_3$	1.35	[0.91, 1.79]	6.05	<.001	Loading	
$TSC = BSCS_4$	0.85	[0.56, 1.14]	5.68	<.001	Loading	
$TSC = BSCS_5$	0.80	[0.49, 1.12]	5.03	<.001	Loading	
$TSC = BSCS_7$	1.32	[0.94, 1.70]	6.78	<.001	Loading	
$TSC = BSCS_8$	1.43	[0.95, 1.90]	5.89	<.001	Loading	
$TSC = BSCS_9$	1.20	[0.80, 1.60]	5.83	<.001	Loading	
$TSC = BSCS_{10}$	1.47	[1.02, 1.92]	6.39	<.001	Loading	
$TSC = BSCS_{12}$	1.18	[0.81, 1.55]	6.26	<.001	Loading	
$TSC = BSCS_{13}$	0.93	[0.61, 1.24]	5.82	<.001	Loading	
$BSCS_5 \sim BSCS_9$	0.01	[-0.06, 0.09]	0.35	0.725	Correlation	
vita_1 ~~ vita_2	0.14	[0.07, 0.22]	3.68	<.001	Correlation	
vita_4 ~~ vita_5	-0.06	[-0.15, 0.02]	-1.39	0.164	Correlation	
$BSCS_5 \sim BSCS_{12}$	0.23	[0.13, 0.32]	4.74	<.001	Correlation	
$BSCS_4 \sim BSCS_5$	0.21	[0.12, 0.30]	4.80	<.001	Correlation	
$BSCS_{12} \sim BSCS_{13}$	0.13	[0.04, 0.23]	2.80	0.005	Correlation	
$BSCS_9 \sim BSCS_{10}$	0.10	[0.00, 0.20]	1.95	0.051	Correlation	
$BSCS_2 \sim BSCS_8$	-0.13	[-0.22, -0.05]	-2.97	0.003	Correlation	
$BSCS_4 \sim BSCS_{13}$	0.16	[0.07, 0.24]	3.49	<.001	Correlation	
$BSCS_9 \sim BSCS_{13}$	0.10	[0.02, 0.18]	2.42	0.015	Correlation	

## Table S5. Vigorous Physical Activity and Sedentary Activity Full Structural Equation Model

$BSCS_3 \sim BSCS_9$	0.04	[-0.06, 0.14]	0.75	0.452	Correlation
BSCS_5 ~~ BSCS_8	0.07	[-0.02, 0.15]	1.48	0.139	Correlation
BSCS_8 ~~ BSCS_9	-0.09	[-0.19, 0.01]	-1.73	0.083	Correlation
$BSCS_5 \sim BSCS_{13}$	0.10	[0.02, 0.19]	2.29	0.022	Correlation
$BSCS_7 \sim BSCS_{12}$	-0.10	[-0.19, -0.02]	-2.31	0.021	Correlation
$BSCS_2 \sim BSCS_{12}$	0.05	[-0.04, 0.14]	0.99	0.322	Correlation
BSCS_8 ~~ BSCS_12	-0.13	[-0.24, -0.03]	-2.51	0.012	Correlation
$BSCS_3 \sim BSCS_8$	-6.46e-03	[-0.12, 0.10]	-0.12	0.908	Correlation
$BSCS_3 \sim BSCS_{12}$	-0.10	[-0.19, -0.01]	-2.22	0.026	Correlation
BSCS_8 ~~ BSCS_10	-0.10	[-0.21, 0.01]	-1.78	0.075	Correlation
$BSCS_2 \sim BSCS_4$	0.06	[-0.02, 0.15]	1.39	0.165	Correlation
BSCS_3 ~~ BSCS_10	-0.07	[-0.18, 0.03]	-1.44	0.149	Correlation
$BSCS_2 \sim BSCS_{13}$	0.04	[-0.05, 0.13]	0.92	0.359	Correlation
vita_3 ~~ vita_5	-0.03	[-0.08, 0.02]	-1.08	0.281	Correlation
SCR ~~ TSC	0.09	[0.04, 0.14]	3.71	< .001	Correlation
sed ~~ mvpa	-0.02	[-0.12, 0.07]	-0.48	0.630	Correlation
SSRT_integration ~~ rt_switch_cost	-0.06	[-0.16, 0.04]	-1.23	0.219	Correlation
SSRT_integration ~~ mean_correctLetters	-0.07	[-0.17, 0.03]	-1.37	0.171	Correlation
<pre>mean_correctLetters ~~ rt_switch_cost</pre>	0.03	[-0.07, 0.13]	0.50	0.615	Correlation
SCR ~ SSRT_integration	0.03	[-0.06, 0.11]	0.59	0.558	Regression
$SCR \sim mean_correctLetters$	0.02	[-0.06, 0.10]	0.48	0.634	Regression
SCR ~ rt_switch_cost	-0.10	[-0.18, -0.01]	-2.28	0.023	Regression
TSC ~ SSRT_integration	-0.02	[-0.06, 0.03]	-0.61	0.542	Regression
$TSC \sim mean_correctLetters$	4.48e-03	[-0.04, 0.05]	0.18	0.858	Regression
$TSC \sim rt_switch_cost$	4.97e-03	[-0.04, 0.05]	0.20	0.842	Regression
ap_vig ~ SSRT_integration	7.42e-04	[-0.09, 0.10]	0.02	0.988	Regression
ap_vig ~ mean_correctLetters	-0.01	[-0.11, 0.08]	-0.26	0.796	Regression
ap_vig ~ rt_switch_cost	-0.10	[-0.19, 0.00]	-1.97	0.049	Regression

an vig~SCR	0 36	[0 23 0 48]	5 69	< 001	Regression	
ap_vig_serv	0.03	[0.20, 0.10]	0.28	0.780	Regression	
ap_vig~15C	0.05	[-0.20, 0.27]	1.00	0.780	Degression	
sed ~ SSR1_integration	-0.00	[-0.13, 0.04]	-1.09	0.275	Regression	
sed ~ mean_correctLetters	-0.01	[-0.11, 0.09]	-0.26	0.793	Regression	
sed ~ rt_switch_cost	0.04	[-0.06, 0.14]	0.74	0.462	Regression	
sed ~ SCR	-0.17	[-0.29, -0.04]	-2.59	0.010	Regression	
sed $\sim TSC$	-0.02	[-0.27, 0.23]	-0.15	0.882	Regression	
ap_vig ~~ sed	0.01	[-0.08, 0.11]	0.31	0.754	Correlation	
Chi2						732.55
Chi2 df						149.00
p_Chi2						0.00
p_Baseline						0.00
GFI						0.90
AGFI						0.84
NFI						0.77
NNFI						0.72
CFI						0.80
RMSEA						0.10
RMSEA_CI_low						0.09
RMSEA_CI_high						0.11
p_RMSEA						0.00
RMR						0.08
SRMR						0.08
RFI						0.67
PNFI						0.54

 PNFI
 0.54

 IFI
 0.81

 RNI
 0.80

Loglikelihood	-10220.75
AIC	20605.49
BIC	20929.45
BIC (adj.)	20669.27

Parameter	Coefficient	95% CI	Z	р	Component	Fit
SCR =~ vita_1	1.00	[1.00, 1.00]		<.001	Loading	
$SCR = vita_2$	1.04	[0.98, 1.11]	31.85	<.001	Loading	
$SCR = vita_3$	0.51	[0.39, 0.63]	8.19	<.001	Loading	
$SCR = vita_4$	1.10	[0.94, 1.25]	14.04	<.001	Loading	
$SCR = vita_5$	1.15	[0.99, 1.31]	14.13	<.001	Loading	
$TSC = BSCS_2$	1.00	[1.00, 1.00]		<.001	Loading	
$TSC = BSCS_3$	1.35	[0.91, 1.79]	6.06	<.001	Loading	
$TSC = BSCS_4$	0.85	[0.56, 1.14]	5.68	<.001	Loading	
$TSC = BSCS_5$	0.80	[0.49, 1.12]	5.03	<.001	Loading	
$TSC = BSCS_7$	1.31	[0.93, 1.69]	6.78	<.001	Loading	
$TSC = BSCS_8$	1.43	[0.95, 1.90]	5.90	<.001	Loading	
$TSC = BSCS_9$	1.20	[0.79, 1.60]	5.83	<.001	Loading	
$TSC = BSCS_{10}$	1.46	[1.01, 1.91]	6.39	<.001	Loading	
$TSC = BSCS_{12}$	1.18	[0.81, 1.55]	6.26	<.001	Loading	
$TSC = BSCS_{13}$	0.92	[0.61, 1.23]	5.82	<.001	Loading	
$BSCS_5 \sim BSCS_9$	0.01	[-0.06, 0.09]	0.36	0.720	Correlation	
vita_1 ~~ vita_2	0.14	[0.06, 0.23]	3.20	0.001	Correlation	
vita_4 $\sim vita_5$	-0.06	[-0.17, 0.04]	-1.22	0.224	Correlation	
$BSCS_5 \sim BSCS_{12}$	0.23	[0.13, 0.32]	4.73	<.001	Correlation	
$BSCS_4 \sim BSCS_5$	0.21	[0.13, 0.30]	4.81	<.001	Correlation	
$BSCS_{12} \sim BSCS_{13}$	0.13	[0.04, 0.23]	2.80	0.005	Correlation	
$BSCS_9 \sim BSCS_{10}$	0.10	[0.00, 0.20]	1.97	0.048	Correlation	
$BSCS_2 \sim BSCS_8$	-0.14	[-0.22, -0.05]	-2.98	0.003	Correlation	
$BSCS_4 \sim BSCS_{13}$	0.16	[0.07, 0.24]	3.50	<.001	Correlation	
$BSCS_9 \sim BSCS_{13}$	0.10	[0.02, 0.18]	2.43	0.015	Correlation	

## Table S6. Moderate Physical Activity and Sedentary Activity Full Structural Equation Model

$BSCS_3 \sim BSCS_9$	0.04	[-0.06, 0.14]	0.74	0.460	Correlation
BSCS_5 ~~ BSCS_8	0.07	[-0.02, 0.15]	1.48	0.139	Correlation
BSCS_8 ~~ BSCS_9	-0.09	[-0.19, 0.01]	-1.74	0.082	Correlation
$BSCS_5 \sim BSCS_{13}$	0.10	[0.02, 0.19]	2.30	0.022	Correlation
$BSCS_7 \sim BSCS_{12}$	-0.10	[-0.19, -0.02]	-2.33	0.020	Correlation
$BSCS_2 \sim BSCS_{12}$	0.04	[-0.05, 0.14]	0.97	0.333	Correlation
$BSCS_8 \sim BSCS_{12}$	-0.13	[-0.24, -0.03]	-2.53	0.011	Correlation
$BSCS_3 \sim BSCS_8$	-8.53e-03	[-0.12, 0.10]	-0.15	0.879	Correlation
$BSCS_3 \sim BSCS_{12}$	-0.10	[-0.19, -0.01]	-2.25	0.024	Correlation
BSCS_8 ~~ BSCS_10	-0.10	[-0.21, 0.01]	-1.77	0.077	Correlation
$BSCS_2 \sim BSCS_4$	0.06	[-0.03, 0.15]	1.38	0.166	Correlation
$BSCS_3 \sim BSCS_{10}$	-0.07	[-0.18, 0.03]	-1.44	0.149	Correlation
$BSCS_2 \sim BSCS_{13}$	0.04	[-0.05, 0.13]	0.92	0.359	Correlation
vita_3 ~~ vita_5	-0.02	[-0.08, 0.03]	-0.89	0.373	Correlation
SCR ~~ TSC	0.09	[0.04, 0.14]	3.69	<.001	Correlation
sed ~~ mvpa	-4.29e-03	[-0.10, 0.09]	-0.09	0.932	Correlation
SSRT_integration ~~ rt_switch_cost	-0.06	[-0.16, 0.04]	-1.23	0.219	Correlation
SSRT_integration ~~ mean_correctLetters	-0.07	[-0.17, 0.03]	-1.37	0.171	Correlation
<pre>mean_correctLetters ~~ rt_switch_cost</pre>	0.03	[-0.07, 0.13]	0.50	0.615	Correlation
SCR ~ SSRT_integration	0.03	[-0.06, 0.11]	0.58	0.559	Regression
$SCR \sim mean_correctLetters$	0.02	[-0.06, 0.10]	0.48	0.630	Regression
SCR ~ rt_switch_cost	-0.10	[-0.18, -0.01]	-2.27	0.023	Regression
TSC ~ SSRT_integration	-0.02	[-0.06, 0.03]	-0.61	0.541	Regression
$TSC \sim mean_correctLetters$	4.37e-03	[-0.04, 0.05]	0.17	0.861	Regression
$TSC \sim rt_switch_cost$	4.99e-03	[-0.04, 0.05]	0.20	0.842	Regression
ap_mod ~ SSRT_integration	0.08	[-0.02, 0.18]	1.57	0.117	Regression
$ap_mod \sim mean_correctLetters$	0.03	[-0.07, 0.13]	0.57	0.568	Regression
ap_mod ~ rt_switch_cost	6.10e-03	[-0.09, 0.11]	0.12	0.905	Regression

ap_mod ~ SCR	0.06	[-0.06, 0.19]	0.96	0.337	Regression
ap_mod ~ TSC	0.07	[-0.18, 0.32]	0.58	0.564	Regression
sed ~ SSRT_integration	-0.06	[-0.16, 0.04]	-1.11	0.268	Regression
sed $\sim$ mean_correctLetters	-0.01	[-0.11, 0.09]	-0.26	0.792	Regression
sed $\sim$ rt_switch_cost	0.04	[-0.06, 0.14]	0.76	0.446	Regression
sed ~ SCR	-0.17	[-0.30, -0.05]	-2.69	0.007	Regression
sed $\sim TSC$	-0.02	[-0.27, 0.23]	-0.16	0.876	Regression
ap_mod $\sim\sim$ sed	-9.38e-03	[-0.11, 0.09]	-0.19	0.851	Correlation

Chi2	421.12
Chi2_df	149.00
p_Chi2	0.00
p_Baseline	0.00
GFI	0.92
AGFI	0.87
NFI	0.85
NNFI	0.85
CFI	0.90
RMSEA	0.07
RMSEA_CI_low	0.06
RMSEA_CI_high	0.08
p_RMSEA	4.10e-05
RMR	0.07
SRMR	0.07
RFI	0.79
PNFI	0.60
IFI	0.90
RNI	0.90

Loglikelihood	-10241.09
AIC	20646.18
BIC	20970.14
BIC (adj.)	20709.96

Parameter	Coefficient	95% CI	Z	р	Component	Fit
SCR =~ vita_1	1.00	[1.00, 1.00]		<.001	Loading	
SCR =~ vita_2	1.04	[0.98, 1.11]	31.85	<.001	Loading	
SCR =~ vita_3	0.51	[0.39, 0.63]	8.18	<.001	Loading	
SCR =~ vita_4	1.09	[0.94, 1.24]	14.04	<.001	Loading	
SCR =~ vita_5	1.14	[0.98, 1.30]	14.16	<.001	Loading	
$TSC = BSCS_2$	1.00	[1.00, 1.00]		<.001	Loading	
$TSC = BSCS_3$	1.34	[0.91, 1.78]	6.04	<.001	Loading	
$TSC = BSCS_4$	0.85	[0.56, 1.15]	5.68	<.001	Loading	
$TSC = BSCS_5$	0.81	[0.49, 1.12]	5.03	<.001	Loading	
$TSC = BSCS_7$	1.32	[0.94, 1.70]	6.78	<.001	Loading	
$TSC = BSCS_8$	1.42	[0.94, 1.89]	5.88	<.001	Loading	
$TSC = BSCS_9$	1.20	[0.80, 1.60]	5.84	<.001	Loading	
$TSC = BSCS_{10}$	1.47	[1.02, 1.92]	6.40	<.001	Loading	
$TSC = BSCS_{12}$	1.18	[0.81, 1.55]	6.26	<.001	Loading	
$TSC = BSCS_{13}$	0.93	[0.62, 1.24]	5.82	<.001	Loading	
$BSCS_5 \sim BSCS_9$	0.01	[-0.06, 0.09]	0.35	0.727	Correlation	
vita_1 ~~ vita_2	0.14	[0.05, 0.23]	3.05	0.002	Correlation	
vita_4 ~~ vita_5	-0.06	[-0.16, 0.05]	-1.09	0.278	Correlation	
$BSCS_5 \sim BSCS_{12}$	0.23	[0.13, 0.32]	4.74	<.001	Correlation	
$BSCS_4 \sim BSCS_5$	0.21	[0.12, 0.30]	4.79	<.001	Correlation	
$BSCS_{12} \sim BSCS_{13}$	0.13	[0.04, 0.23]	2.79	0.005	Correlation	
$BSCS_9 \sim BSCS_{10}$	0.10	[0.00, 0.20]	1.95	0.052	Correlation	
$BSCS_2 \sim BSCS_8$	-0.13	[-0.22, -0.04]	-2.93	0.003	Correlation	
$BSCS_4 \sim BSCS_{13}$	0.15	[0.07, 0.24]	3.47	<.001	Correlation	
$BSCS_9 \sim BSCS_{13}$	0.10	[0.02, 0.18]	2.42	0.016	Correlation	

## Table S7. Walking and Sedentary Activity Full Structural Equation Model

$BSCS_3 \sim BSCS_9$	0.04	[-0.06, 0.14]	0.79	0.430	Correlation
BSCS_5 ~~ BSCS_8	0.07	[-0.02, 0.15]	1.50	0.133	Correlation
$BSCS_8 \sim BSCS_9$	-0.09	[-0.19, 0.01]	-1.69	0.091	Correlation
$BSCS_5 \sim BSCS_{13}$	0.10	[0.01, 0.19]	2.28	0.023	Correlation
$BSCS_7 \sim BSCS_{12}$	-0.10	[-0.19, -0.02]	-2.31	0.021	Correlation
$BSCS_2 \sim BSCS_{12}$	0.05	[-0.04, 0.14]	1.00	0.319	Correlation
$BSCS_8 \sim BSCS_{12}$	-0.13	[-0.23, -0.03]	-2.47	0.013	Correlation
$BSCS_3 \sim BSCS_8$	-1.13e-03	[-0.11, 0.11]	-0.02	0.984	Correlation
$BSCS_3 \sim BSCS_{12}$	-0.10	[-0.19, -0.01]	-2.19	0.028	Correlation
BSCS_8 ~~ BSCS_10	-0.10	[-0.20, 0.01]	-1.74	0.082	Correlation
$BSCS_2 \sim BSCS_4$	0.06	[-0.03, 0.15]	1.38	0.167	Correlation
$BSCS_3 \sim BSCS_{10}$	-0.07	[-0.17, 0.03]	-1.41	0.158	Correlation
$BSCS_2 \sim BSCS_{13}$	0.04	[-0.05, 0.13]	0.91	0.362	Correlation
vita_3 ~~ vita_5	-0.02	[-0.08, 0.03]	-0.81	0.418	Correlation
SCR ~~ TSC	0.09	[0.04, 0.14]	3.69	<.001	Correlation
sed ~~ ap_mod	-9.88e-03	[-0.11, 0.09]	-0.20	0.844	Correlation
SSRT_integration ~~ rt_switch_cost	-0.06	[-0.16, 0.04]	-1.23	0.219	Correlation
SSRT_integration ~~ mean_correctLetters	-0.07	[-0.17, 0.03]	-1.37	0.171	Correlation
<pre>mean_correctLetters ~~ rt_switch_cost</pre>	0.03	[-0.07, 0.13]	0.50	0.615	Correlation
SCR ~ SSRT_integration	0.03	[-0.06, 0.11]	0.59	0.555	Regression
$SCR \sim mean_correctLetters$	0.02	[-0.06, 0.11]	0.50	0.620	Regression
SCR ~ rt_switch_cost	-0.10	[-0.19, -0.01]	-2.29	0.022	Regression
TSC ~ SSRT_integration	-0.02	[-0.06, 0.03]	-0.61	0.542	Regression
$TSC \sim mean_correctLetters$	4.61e-03	[-0.04, 0.05]	0.18	0.854	Regression
$TSC \sim rt_switch_cost$	5.00e-03	[-0.04, 0.05]	0.20	0.842	Regression
ap_marche ~ SSRT_integration	0.08	[-0.02, 0.18]	1.49	0.135	Regression
ap_marche ~ mean_correctLetters	0.01	[-0.09, 0.11]	0.24	0.810	Regression
ap_marche ~ rt_switch_cost	0.03	[-0.07, 0.13]	0.59	0.558	Regression

ap_marche ~ SCR	-0.05	[-0.18, 0.08]	-0.77	0.442	Regression
ap_marche ~ TSC	-0.06	[-0.31, 0.19]	-0.46	0.649	Regression
sed ~ SSRT_integration	-0.06	[-0.15, 0.04]	-1.09	0.274	Regression
$sed \sim mean_correctLetters$	-0.01	[-0.11, 0.09]	-0.26	0.798	Regression
sed $\sim$ rt_switch_cost	0.04	[-0.06, 0.14]	0.77	0.443	Regression
sed ~ SCR	-0.17	[-0.30, -0.05]	-2.69	0.007	Regression
sed $\sim TSC$	-0.02	[-0.27, 0.23]	-0.16	0.871	Regression
ap_marche ~~ sed	-0.01	[-0.11, 0.09]	-0.22	0.829	Correlation

Chi2	193.59
Chi2_df	149.00
p_Chi2	8.19e-03
p_Baseline	0.00
GFI	0.96
AGFI	0.93
NFI	0.92
NNFI	0.97
CFI	0.98
RMSEA	0.03
RMSEA_CI_low	0.01
RMSEA_CI_high	0.04
p_RMSEA	1.00
RMR	0.04
SRMR	0.04
RFI	0.89
PNFI	0.66
IFI	0.98
RNI	0.98

Loglikelihood	-10241.80
AIC	20647.59
BIC	20971.54
BIC (adj.)	20711.37