Title

Does Short Term Activity Engagement Affect Processing Speed?

Author

Azeem, Rehman

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DOES SHORT TERM ACTIVITY ENGAGEMENT AFFECT PROCESSING SPEED?

By

Rehman Azeem

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APPROVED

Dr. Chandra Reynolds
Department of Psychology

Dr. Richard Cardullo, Howard H Hays Jr. Chair, University Honors

Abstract

The basis of this scientific study was to examine whether different types of activities benefit cognitive abilities such as processing speed. Processing speed is a measure of how fast an individual can complete a mental task, and prior work has shown peak speed performance in early adulthood with steady declines across the adult lifespan. Studies of adult cognition aim to evaluate how to maintain retention, how to increase working memory, and problem-solving skills. Among factors that influence speed of processing, activity engagement may represent avenues of possible intervention. This study made use of already-collected data on undergraduate students that were placed into three different activity groups: physical activities, social activities, and a control group. Across a 2-week period, the physical and social activity participants were asked to perform an extra ten minutes worth of physical or social activities each day of their own choosing, respectively, such as playing a sport or simply walking, or to interact with people in a manner of their own choosing. Alongside completing surveys, participants performed cognitive tasks downloaded on a phone provided to them twice each day. We examined processing speed duration, where we expected to see differential effects by activity condition, that daily physical activity engagement would predict processing speed regardless of condition, and that those in the physical activity condition would benefit the most in terms of improved processing speed. We observed that individuals in the physical activity condition that engaged in more daily physical activity benefitted in terms of reduced processing speed duration suggesting that short-term interventions may result in visible benefits to cognitive processing speed in college students.

Many studies have investigated whether processing speed can be shaped by different events or activities an individual may experience. Processing speed refers to how long an individual takes to perform a mental activity, e.g., how long it may take an individual to come up with an answer to “2+2”. Processing speed may support many executive cognitive functions such as working memory (Salthouse, 1996) that individuals use in day to day normal activities. Many studies have assessed processing speed in different situations and variables. For example, Mella et al (2015) compared two different age groups (9-12 years, 56-89 years) on processing speed observing that processing speed tended to be faster in younger cohort individuals than older cohort individuals. Younger cohort individuals may have higher processing speed for many reasons. For example, Craik and Bialystok (2006) reported that individuals with high cognitive functioning at younger ages tend to seek out new learning concepts and learn new skills. These new concepts and skills include learning a new language, learning how to play an instrument, and playing new games that enhance their cognitive capacity, which may decline in later ages. This learning curve tends to decline as an individual age (Salthouse, 1996). The learning tends to decrease because the individual’s processing speed declines as they become older (Salthouse, 1996). Salthouse (1996) hypothesized that this could possibly be an effect of loss of neuronal pathways and loss of myelin in the pathway of the axon (during an action potential).

Other researchers have focused their research efforts to better understand how to improve processing speed. For example, a report from the Victoria Longitudinal Study focused on whether processing speed would change based on self-reported engagement in physical, social, and cognitive activities (Bielak et al., 2007) during a six-year longitudinal follow-up of adults aged 55 to 94 years. The authors found a positive correlation between completing challenging cognitive tasks with better performance on processing speed tasks. Other studies employing cognitive training have found that older individuals are able to improve their processing speed with training (Ball, Edwards, & Ross, 2007), where each assessment became more difficult than the last to help ensure improvement. These investigators concluded that processing speed can be improved using computerized training assessments that help represent scenarios found in the real world (Ball, Edwards, & Ross, 2007). A study called the Advanced Cognitive Training for Independent and Vital Elderly (ACTIVE) enrolled individuals ages 65-94 in computerized training sessions (Ball et al., 2013). Altogether, eighteen speed-of-processing training (SOPT) sessions (i.e., 10 training sessions, 4 plus 4 booster sessions at 11 and 35-months, respectively) were conducted for those enrolled in the speed intervention group where the computerized program was meant to enhance mental quickness using visual and auditory tasks. Indeed, participants who were the most adherent to the training showed better maintained speed of processing. A ten-year follow-up study of ACTIVE participants confirmed and extended the 5-year findings showing that engaging in as few as ten SOPT sessions led to notable improvements in processing speed, with long lasting effects from training five years ago (Rebok et al., 2014). Moreover, participants the speed training group, as well as the other training groups, showed less decline in instrumental activities of daily living across 10 years (Rebok et al., 2014), benefitting everyday functioning.

Activity Domains & Processing Speed

Activity engagement studies focused on processing speed suggest that cognitive activity and cognitive training (e.g., Bielak et al., 2007; Bielak et al., 2007, Rebok et al, 2014) are beneficial, whereas self-reported associations with other activity engagement domains are less clear (e.g., Bielak et al., 2007). However, a study suggests that women ages 57-85 showed enhanced cognitive processing speed if they partook in aerobic exercises (Rikli & Edwards, 1991). The study continued for three years and reported that women who participated in the aerobic exercise group (stretches and yoga) had better reaction time and processing speed scores than the control group (who did not exercise at all). Performing these physical activities is associated with better processing speed at older ages too and may help to delay decline in information processing speed as well (Dik et al., 2003). Dik et al (2003) looked at the physical activities' individuals reported retrospectively taking part in between the ages of 15-25 and compared it to the processing speed when individuals were 62-85 years of age. Results of this study suggested that partaking in physical activities at an early age may prevent or slow down the decline in information processing speed as an individual gets older.

Similar to participating in physical activities, engagement in social activities appears to benefit processing speed. For example, individuals that participated in music classes were shown to have an increase in processing speed, cognitive control, and verbal fluency (Bugos, 2010). Individuals included in this study were 60-85 years of age and participated in music classes for sixteen weeks. Social activities in this study included a group conversational piano music class, and music listening instruction. Participants listened to music together as a group and conversed on what they felt about the music.

Other studies have observed the positive effects of cognitive activity engagement on processing speed beyond the Bielak et al. (2007) described above. For example, previous research has found that playing cognitive games can help improve cognitive function and processing speed (Nouchi et al., 2012). Nouchi et al (2012) engaged 28 older cognitively-intact Japanese adults where 14 participants played either a Nintendo game called 'Brain Age' which included performing calculations and reading parts of books out loud for 15 minutes a day for 20 days compared to 14 adults in the control group who played ‘Tetris’. Participants who played Brain Age versus Tetris show improvements in executive functioning and processing speed. Games that help improve processing speed are not only limited to games that employ calculations and reading, but also extends to action console games (Zhang & Kaufman, 2016). For example, playing action games and role-playing games showed moderate to large effect sizes in older individuals living in nursing homes with respect to processing speed (Zhang & Kaufman, 2016).

Current Study

The primary focus of this present study is on processing speed and engagement in activities from different activity domains (cognitive, social, physical) in a sample of young adult college students. The main purpose of this present study is to assess whether participating in activities from multiple activity domains (physical, social) leads to improvements in processing speed beyond participating in cognitive activities. The present study hypothesizes that there will be differential effects on processing speed depending on the activity domain (cognitive, social, physical). Additionally, this study hypothesizes that engagement in physical activities will affect cognitive speed irrespective of condition. Lastly, the study hypothesized that those in the physical condition may benefit the most from additional engagement in physical activities.

Methods

Participants

The sample was collected during October and November of 2016 to analyze the effects of cognitive abilities throughout different engagement activities. Of 96 participants enrolled in the experiment, only 92 individuals were included in the study due to failure to complete the consent forms or the baseline survey. The sample composition was predominantly female (71 females, 21 males). The age range was diverse ranging from eighteen to thirty years old (*M*=19.13; SD=2.00; ages 18-30). This experiment was conducted at an accredited postsecondary minority-serving institution, with a diverse participant sample (Asian = 39, African-American = 4, Hispanic/LatinX = 36, White = 10, and other = 3). The ambulatory cognitive assessments took place on Android mobile phones (Motorola Droid X; Motorola, Inc., Schaumburg, Illinois) which were provided by the proctoring lab. Participants were administered a baseline questionnaire, which consisted of demographics such as age and gender. Descriptive statistics are shown in Table 1.

Measures

Shipley Assessment. The Shipley assessment (Shipley, 1940), which consisted of the Vocabulary and the Abstraction scales was administered online. For the vocabulary portion, participants were shown a word and asked to select from four options which word meant the same thing, or most nearly the same thing, as the first word. For example, participants were shown the word ‘permit’ and asked to select which of four words was most similar. The test became harder as the participants went on answering questions. For the abstraction portion of the assessment, participants were shown a series of critical thinking sequences and were asked to complete them (guided by a dash). For example, participants could’ve come across numeric sequences such as “1, 2, 3,4, 5, - “, and were asked to complete the value that was replaced with a dash. The test was scored as being correct, incorrect or missing. All correct answers were summed up to receive a total score for an individual participant. Participants who did not complete 10% of the items in their assessment had their total score set to missing. Descriptives of these measures can be seen in Table 1.

Randomization. Participants were randomly put into three different groups consisting of the social, physical, and cognitive control groups. The social group consisted of participants that had to complete an extra social task such as talking to a friend for an extra 10 minutes than they already did each day. Physical group participants were asked to complete an extra physical activity of 10 minutes than they already would. For example, the participants can run for an extra 10 minutes each day. The cognitive task group were not asked to do any extra activity other than to play the the cognitive games that all participants were asked to play.

Leisure Time Activity Questionnaire. The Leisure Time Activity questionnaire was designed to assess how individuals spend their leisure time (see Haberstick, Zeiger, & Corley, 2014). Example items are "How many hours per week do you spend practicing different physical activities?" and "How many hours per week do you spend doing things with a club?" Participants answered on a 8-point Likert scale that was recoded to hours, from 0= None, 1= 1 hour or less per week, 2.5=2-3 hours per week, 4.5 = 4-5 hours a week, 5.5= 5-6 hours per week, 6.5 = 6-7 hours per week, 7.5= 7-8 hours per week, 8=8 or more hours per week, or Would Rather Not Answer.

Baseline physical activity engagement (BASE_PA) was formed by summing across five items that asked about hours spent: (1) *practicing different physical activities (like shooting baskets or working on dance routines)*? (2) *taking part in an organized sport or recreation program*, (3) *working out as part of a personal exercise program (like running or biking),* (4) P*laying pickup games like basketball, touch football, etc.*, (5) *Doing activities with a pet*. After summing across items, the resulting sums were coded into minutes per day and square root transformed (see Table 1).

Momentary Assessment

Morning & Evening Surveys. The survey protocol employed an ecological momentary assessment (EMA) approach similar to the ESCAPE study (Scott et al., 2015) but with survey content adapted to the current study and administered via SurveyMonkey (SVMK Inc., San Mateo, CA). The momentary assessment questionnaire was given to participants via a link sent to them through text message twice daily (once in mid-morning & once in mid-evening) to assess how much time they were spending on different activities. Participants did not have a time limit to respond to their surveys but were instructed to respond as soon as they could. The present study's daily survey assessment differed from ESCAPE, by asking questions such as "How much time have you spent on cognitive activities today?" and "How much time have you spent on physical activities since the last time you completed a questionnaire?" (scored by the number of minutes participants entered). Participants were asked to report separately the minutes of activity spent on daily personal cardio routine, daily personal strength training routine, or daily personal yoga/pilates/stretching routines, but the current study only evaluated the response to the total minutes spent on physical activities.

The daily assessment of physical activity was coded by summing across both daily survey assessments. We removed 3 outlying or text-based rather than numeric entries and winsorized 54 values outside of 3 *SD* for the morning (upper value = 189.92 minutes) and evening surveys (upper value = 213.22 minutes). For purposes of analysis, values were summed within each day. Next, the geometric mean of the 14-day total reports of physical activity engagement (EMA_PA) was calculated and square rooted for each participant to serve as a predictor in multilevel models (see Table 1). Descriptive statistics for the daily physical activity surveys are shown in Table 2, for those who did both daily cognitive and survey assessments (*N*=76).

<u>*Cognitive Assessment*</u>. All groups of participants were asked to complete cognitive assessments, which assessed the participant's ambulatory cognitive performance identical to the ESCAPE study (Scott et al., 2015) but with two daily assessments instead of five. The cognitive assessments employed a game-like task for each cognitive domain (processing speed, spatial working memory, and verbal working memory) and performance on each included score related to accuracy and duration. All three tasks checked tapped a different cognitive ability as described in the ESCAPE study (Scott et al., 2015). In the Symbol Search task, participants were required to match a symbol that they saw at the bottom of the screen to the symbol on the top of the screen (processing speed) as fast as possible. The location memory task required participants to memorize the position of three red dots presented for 3 *s* on a 5-by5 grid and indicate the position of dots after an intervening filler task. The last task required participants to match two playing cards that were facing up to two cards face down (2-back task), in addition to trials where all cards were shown and asked whether cards in the boxes simply matched (0-back task).

This present study's main focus was to examine processing speed via the Symbol Search task. Processing speed is the cognitive ability to recognize received information and complete a mental task in relation to speed. Hence, we evaluated duration (in seconds, *s*) as the outcome, across the two daily trials for 14 days or 28 total possible trials. We removed 87 outlying values within persons prior to analysis. Descriptive statistics for the Symbol Search duration by day are shown in Table 2.

Procedure

On the first day of the experiment, participants were given consent form to complete before the baseline survey was administered. They were then given a baseline survey, which took about 60 minutes to complete. The baseline survey included demographics, Weekly Activity Engagement Survey (including the Leisure Time Activity Questionnaire) and Shipley cognitive assessment. A link to the baseline survey was texted to the participant's cell phone via Survey Monkey (SVMK Inc., San Mateo, CA).

Once completing the baseline survey, participants were loaned a cell phone (Motorola Droid X; Motorola, Inc., Schaumburg, Illinois) which only allowed them to complete the daily cognitive tasks. Participants were texted a link twice daily starting the morning after the baseline measure that directed them to the momentary assessment. They completed mid-morning and evening surveys, which took the participants about twenty-five minutes to complete per day. The surveys included questions such as "How much time have you spent on social activities today" and the participants responded by putting in the number of minutes. This survey helps to keep track of the types of activities the participants are partaking in as well as comparing it to cognitive performance. Participants approximately spent up to ten minutes per day on the momentary assessments.

After participants completed their consent forms, they were randomly assigned to one of three experimental groups (social, physical, or control). The social group completed ten minutes more of any social activity of their choice. This could include anything such as talking to friends or conversing with family members for ten more minutes. The physical group were asked to complete an extra 10 minutes' worth of physical activities than they already do. Activities in this group include running or lifting weights for 10 minutes more than per usual. The control group was told to participate in activities that they usually do on a daily basis.

Lastly, cognitive tasks were given to all participants regardless of what experimental group they were in. These tasks were given through phones that were checked out to all participants through the Biobehavioral Research Lab. Participants were told to do these tasks twice daily for fourteen days.

After the fourteenth day of the experiment, participants received an electronic debriefing form and instructions on how to return the lab's phones.

Statistical Analysis

Chi-square, t-tests, and Analysis of variance (ANOVA) were used to test for differences in socio-demographics and other baseline characteristics between the three conditions. SPSS version 26 was used (IBM, Inc.;Armonk, NY).

A series of multi-level models were fitted, first to test the shape of Symbol Search duration, and then to test hypotheses using SAS Proc Mixed 9.4 (SAS Inc. Cary, NC). Specifically, unconditional no-growth, linear and quadratic models were fitted (Grimm, Ram & Estabrook, 2016), where the models accounted for the observations nested within individuals across the 14 days. Both fixed and random effects were estimated using full maximum-likelihood estimation. Model fit statistics included the Log-likelihood Ratio Test (LRT), Akaike's Information Criterion (AIC; Akaike, 1987) were used to compare each model tested. LRT is the difference between the $-2\ln(L)$ value between two nested models tested that differ on the number the parameters fitted. LRT is distributed as a *chi-square* (χ^2) and is known as the goodness-of-fit test. The AIC was calculated as the log-likelihood with the addition of twice the number of the parameters and is denoted as $2\ln(L)+2k$ where k denotes to the number of parameters in a model.

Better fitting models are indicated by a significant increase in goodness-of-fit based on the LRT and lower AIC values. Given the number of covariates entered for adjustment, we prioritized the fixed effects parameter tests where parameters were divided by their standard errors to evaluate significance (Singer & Willet, 2003).

The quadratic model was chosen as best-fitting whereupon conditional models were fitted adding fixed-effect predictors of condition, then the baseline physical activity measure (Base_PA) and the geometric mean of the 14-day reports of physical activity engagement (EMA_PA) as predictors of the growth features for Symbol Search duration. Last, condition by activity interactions were included. Parameters, standard errors, and associated significance and goodness of fit tests are reported for fixed effect parameters for conditional models in addition to random effect parameter values.

Results

Prior to hypothesis testing, we assessed whether there were any differences in socio-demographics and other baseline characteristics between the three conditions. Neither sex [$\square^2(2) = 0.38$, $p = 0.83$] nor ethnicity [$\square^2(8) = 8.07$, $p = 0.43$], nor age [$F(2,89)=0.03$, $p=0.97$] differed significantly by condition. Moreover, average engagement in physical activities (hours per week) at baseline [$F(2,89)=0.03$, $p=0.97$], did not differ across the three different conditions.

Performance on the Shipley Assessment Scales (Abstract and Vocab) were considered next. While Abstract scores were non-significant [$F(2,89)=0.50$, $p=0.61$] across the three different conditions, Vocab scores were significantly different [$F(2,89)=3.58$, $p=0.03$] across the three conditions. A follow-up *t*-test was conducted to examine the mean differences across conditions. Participants in the social condition ($M=26.40$, $SD= 3.79$) had a lower average score than participants in the physical condition ($M=28.97$, $SD=3.81$) [$t(60)=2.64$, $p=0.01$]. The cognitive control condition (*M*=28.03, *SD*=3.80) did not differ significantly from the other two conditions (both $p \geq 0.10$).

In addition to reporting baseline activity engagement (BASE_PA), the amount of physical activity was reported daily for each participant during the fourteen-day period regardless of their condition (EMA_PA). We observed that the geometric mean of EMA_PA varied based on condition at trend significance [F (2,89)=2.37, p=0.099]. EMA_PA was higher in the physical condition versus the other two conditions at trend significance [F (1,90)=3.85, p=0.053].

A preliminary correlation was done of BASE_PA and Symbol Search duration to evaluate whether all participants were randomized, observing r (1844) = - 0.086, p < 0.00. However, a multilevel regression analysis accounting for clustering of Symbol Search duration scores within individuals was non-significant meaning that all individuals were randomized (b = -.26, se =.22, p = 0.235). A preliminary correlation was done of EMA_PA and Symbol Search duration, observing r (1844) = - 0.066, p < 0.00. Another multilevel regression suggested the association was non-significant suggesting that EMA_PA did not significantly predict reduced duration (b = -.17, se =.18, p =0.337).

Next, a correlation was run between the BASE_PA and first occasion EMA_PA to assess the association in the amount of physical activity engagement at baseline with the first study day physical activity engagement. The correlation was non-significant [r (74)=-0.079, p=0.50]. Lastly, other correlations of baseline demographics with their first study day trial of symbol search are reported in Table 3.

Multilevel analysis. Before entering predictors to test hypotheses, we modelled the shape of Symbol Search duration trajectories where a quadratic model fitted best. Figure 1 shows the general expected curve across all 76 participants, where on day 7, participants showed an average duration of 26.03 *s* (*se* = .82), a linear trend on day 7 of -.25 *s* (*se* = .06) but that downward trend is dampened by .02 *s* (*se* = .01) across days (squared) (see Table 4, Model 0).

To test hypothesis 1, we entered Condition (Social/Cognitive = 0, Physical =1) as a predictor of performance on day 7 (Intercept), linear change on day 7, and quadratic change across days (Nonlinear change), adjusting for Vocab and Vocab x Condition on performance on day 7. Condition was not a significant predictor of performance (b=-1.74, se=1.68, p>0.05) or linear change on day 7 (b=0.16, se=0.13, p>0.05), or quadratic change across days (b=-0.04, se=0.03, p>0.05) (See Table 4, Model 1).

To test hypothesis 2, we first entered BASE_PA which did not significantly predict performance (b=-0.22, se=0.25, p>0.05) or linear change on day 7 (b=0.007, se=0.01, p>0.05), or quadratic change across days (b=-0.003, se=0.004, p>0.05) (See Table 4, Model 2). Next, we added EMA_PA which did not significantly predict performance (b=-0.16, se=0.22, p>0.05) or linear change on day 7 (b=0.03, se=0.02, p>0.05), or quadratic change across days (b=-0.002, se=0.004, p>0.05) (See Table 4, Model 3).

To test hypothesis 3, we entered BASE_PA and EMA_PA by Condition, adjusting for Vocab (see Model 4). EMA_PA significantly predicted linear change in symbol search duration on day 7 (b=0.05, se=0.02). Moreover, EMA_PA by Condition was significant suggesting that those who were in the physical activity condition benefitted in terms of faster reduction in duration (b=-0.07, se=0.04). Next, nonlinear change by Condition was significant suggesting that those who were in the physical activity condition experienced less dampening of the speed gains (reductions in duration) across days (b=-0.06, se=0.03). All other parameters are reported in Table 4. Participants in the physical activity condition showed faster performance across days (reduced Symbol Search duration) than those in the control and social conditions (see Figure 2). Moreover, greater EMA_PA engagement led to faster performance (c.f. 20 vs. 40 minutes, see Figure 2).

Discussion

The present study examined whether partaking in physical activities helped individuals process and react to information faster in everyday contexts. Overall, we expected that physical activity engagement would predict reduced processing speed times vis-à-vis quicker reaction times. We examined processing speed duration in different activity engagement groups across a 2-week period in participants' day-to-day context, where we expected to see differential effects by activity condition, that daily physical activity engagement would affect processing speed regardless of condition, and that those in the physical activity condition would benefit the most in terms of improved processing speed.

The current study found that while condition and baseline or daily physical activity were not significant as individual predictors, individuals in the physical activity condition who engaged in more daily physical activity benefitted in terms of reduced processing speed duration. Therefore, individuals who were placed in the physical activity condition had larger reductions in symbol search duration with increased minutes of daily activity engagement across the two-week period. Similar to other studies, findings have shown that processing speed may benefit from engagement in cardiovascular activities (Tam, 2013). Cardiovascular activities included running, walking, and climbing stairs, similar to the kinds of activities participants reported on in the present study.

Contrastingly, other studies have found that physical activities do not show larger improvements than other activity engagements. For example, a similar study found that complex cognitive tasks and cognitive training show larger improvements throughout a six-year longitudinal study than self-reported physical and social activities (Bielak et al., 2007).

The present study was conducted on college- aged students; however, our results are consistent with studies of older individuals. For example, the findings in Frederiksen et al (2015) where participants were on average 73 years old reported an association between physical activity engagement and better cognitive performance at baseline and at a 3-year follow-up consistent with greater maintenance of executive functioning and processing speed. Similarly, a cross-sectional study of individuals 62-85 years showed that those retrospectively reporting higher engagement in physical activities when they were 15 and 25 years of age tended to show better processing speed performance (Dik et al., 2003). The studies also suggest that partaking in physical activities at a younger age may slow information processing declines in individuals as they get older.

Improving processing speed through activity engagement may have significant intervention potential.   For example, improving processing speed may be beneficial to individuals as they age and may be able to delay (and possibly prevent) mental health disorders such as depression (Sheline et al., 2006). Caregivers may potentially help children perform better in school by building their processing speed, which is correlated to their working memory (Fry & Hale, 2000).

The present study included a physical activity group that completed additional ten minutes worth of any physical activities. However, the study did not specify what physical activities to do or complete during their day. Participants could report the minutes of activity spent on cardio-related, strength training, or yoga/stretching personal routines, but no particular activity was encouraged nor were these evaluated in the current study. Another limitation seen in the present study was that it focused on college students. Therefore, the study's findings cannot be generalized beyond the college population. Attending college could have been another way that individuals sharpened their processing speed alongside partaking in the experiment.

In future studies, other researchers might account for a few variables that the present study did not account for including isolating specific physical activities that each participant completed during their daily activities. Future studies ought to recruit both college students and individuals that are similar in age but do not attend higher education after high school. Having broader representation of young adults may make such a study more generalizable and parse the benefits of activity engagement on processing speed for those pursuing higher education versus those who directly take on occupational pursuits.

In summary, we observed that additional physical activity engagement in a short-term intervention appears to benefit processing speed measured in everyday contexts, beyond additional social activity or no additional activity engagement, among college-aged individuals. Whether increased physical activity engagement in a short-term intervention has any lasting effect is unclear. However, findings from lifespan studies suggest that activity engagement may be predictive of late-life cognitive functioning perhaps because it may reflect long-term patterns of engagement that benefit cumulatively into late-life. Future studies should focus on specific physical activities that may differentially benefit cognitive functioning such as processing speed.

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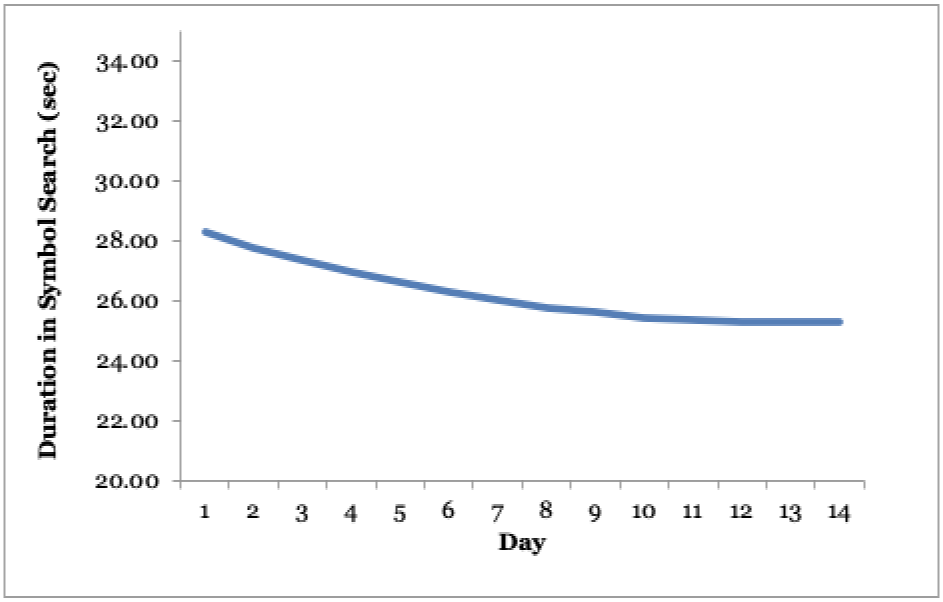
Figure 1

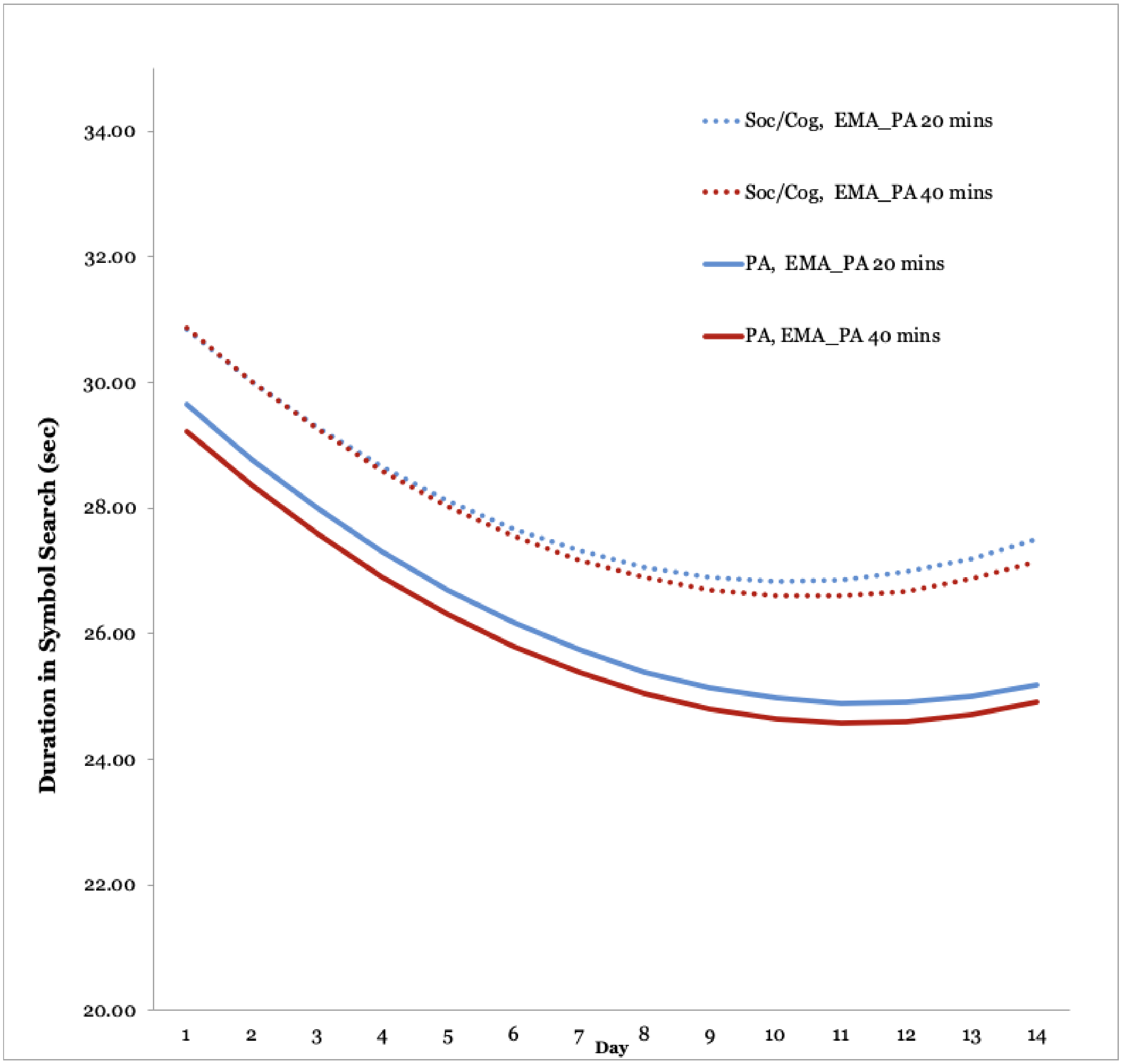
Symbol Search Duration Across 14 Days.



Note: The figure shows a decrease in participants' Symbol Search duration (in seconds) across condition.

Figure 2

Symbol Search Duration across all 14 Days by Condition and Daily Physical Activity Engagement.



Note: The Figure shows progression in Symbol Search duration (in seconds) by condition and mean amount of daily physical activity (EMA_PA) completed, i.e., geometric mean of minutes per day across 14 days. Social and Cognitive (Control) conditions were grouped together (Soc/Cog) and compared to the Physical Activity condition (PA).

Table 1

Descriptive statistics by condition.

	Physical (31)		Social (30)		Cognitive (31)	
Variables	***M***	***SD***	***M***	***SD***	***M***	***SD***
Age	19.19	1.38	19.13	2.32	19.06	2.25
Sex	0.34	0.41	0.33	0.43	0.34	0.45
Abstract	15.89	2.69	15.11	3.34	15.39	3.19
Vocab	28.97	3.81	26.40	3.79	28.03	3.80
Base_PA	7.08	3.48	7.10	3.89	7.41	3.16
EMA_PA	6.66	3.47	5.54	3.34	4.65	4.05

Note. Abstract = Shipley Abstraction Scale; Vocab = Shipley Vocabulary Scale; Base_PA = baseline physical activity, reported in minutes per day and square root transformed; EMA_PA = geometric mean of ecological momentary assessment of physical activity across 14 days, reported in minutes per day and square root transformed.

Table 2

Symbol Search duration and EMA daily physical activities across 14 days with outliers removed.

	Day	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**
Assessment	*N*	147	144	140	126	137	135	133	132	134	123	122	127	127	119
SS Duration (*s*)	*M*	27.54	28.20	26.94	27.38	27.33	26.45	25.49	25.97	25.46	25.87	25.89	25.15	26.05	25.68
	SD	8.52	9.69	9.55	9.24	10.75	9.78	9.35	9.60	9.59	8.90	10.03	8.58	10.25	10.52
EMA_PA	*M*	1.52	1.47	1.41	1.10	1.47	1.29	1.42	1.41	1.35	1.26	1.33	1.33	1.49	1.12
	SD	3.24	3.21	3.19	3.14	3.20	3.16	3.21	3.17	3.21	3.16	3.18	3.21	3.24	3.17

Note. 76 unique individuals contributed up to two scores per day. SS Duration = Symbol Search duration in seconds (*s*); EMA_PA = ecological momentary assessment of physical activities, geometric mean across 14 days, scored in minutes per day, squared rooted and centered on 5.477 (equivalent to 30 minutes).

Table 3

Correlation Among Baseline Demographics and First Symbol Search Trial Duration.

Variables	***r***	***p***
Gender	0.060	0.607
Age	-0.055	0.639
Abstract	0.071	0.543
Vocab	0.147	0.207
Base_PA	-0.117	0.319

Note: N=75. One participant did not start their first trial until day 9, and hence they were excluded from this table. Abstract = Shipley Abstraction Scale; Vocab = Shipley Vocabulary Scale; Base_PA = baseline physical activity, reported in minutes per day and square root transformed.

Table 4

Multilevel growth model results.

		Quadratic	+ Condition, Vocab	+ Base_ PA	+ EMA_PA	+ By Condition
	Parameter	**Model 0**	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Fixed Effects						
Status at day 7, b1i	b_{01}	26.03 (.82)*	26.79 (.99)*	26.41 (0.88)*	26.48 (0.89)*	27.24 (1.1)*
Condition (PA = 1)	b_{11}		-1.74 (1.68)			-1.70 (1.90)
Vocab (Centered = 27.91)	b_{21}		0.54 (0.21)*	0.337 (0.17)	0.35 (0.17)*	0.53 (0.20)*
Vocab X Condition	b_{31}		-0.31 (0.37)			-0.31 (0.36)
Base_PA (Centered sqrt(30mins))	b_{41}			-0.22 (0.25)	-0.23 (0.25)	-0.29 (0.32)
Base_PA X Condition	b_{51}					0.10 (0.50)
EMA_PA (Centered sqrt(30mins))	b_{61}				-0.16 (0.22)	-0.077 (0.27)
EMA_PA X Condition	b_{71}					-0.12 (0.46)
Linear change at day 7, b2i	b_{02}	-0.25 (0.06)*	-0.31 (0.08)*	-0.26 (0.069)*	-0.28 (0.07)*	-0.32 (0.08)*
Condition	b_{12}		0.16 (0.13)			0.19 (0.14)
Base_PA	b_{22}			0.0069 (0.012)	0.008 (0.02)	0.0096 (0.025)
Base_PA X Condition	b_{32}					0.0006 (0.038)
EMA_PA	b_{42}				0.029 (0.017)	0.05 (0.02)*
EMA_PA X Condition	b_{52}					-0.07 (0.035)*
Nonlinear change, b3i	b_{03}	0.021 (0.013)	0.037 (0.016)*	0.025 (0.014)	0.026 (0.014)	0.047 (0.017)*
Condition	b_{13}		-0.04 (0.026)			-0.06 (0.028)*
Base_PA	b_{23}			-0.003 (0.004)	-0.004 (0.004)	-0.008 (0.005)
Base_PA X Condition	b_{33}					0.009 (0.008)
EMA_PA	b_{43}				-0.0016 (0.0035)	-0.003 (0.004)
EMA_PA X Condition	b_{53}					0.0066 (0.007)

		Quadratic	+ Condition, Vocab	+ Base_ PA	+ EMA_PA	+ By Condition
	Parameter	**Model 0**	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Random Effects						
Level 1 (residual)	s^2_u	51.33	51.28	51.30	51.28	51.25
Level 2	s^2_1	46.36	41.96	43.12	42.94	41.23
	s_{21}	0.72	0.75	0.73	0.80	0.82
	s^2_2	0.13	0.12	0.13	0.12	0.10
	s_{31}	-0.22	-0.22	-0.21	-0.22	-0.23
	s_{32}	-0.0087	-0.0078	-0.0084	-0.0078	-0.0060
	s^2_3	0.0021	0.0019	0.0020	0.0020	0.0014
Model Fit						
Goodness-of-fit	-2LL	12783.7	12770.7	12776.6	12772.3	12757.3
	AIC	12803.7	12800.7	12804.6	12806.3	12811.3
Model Comparison	---	---	Model 0 - Model 1	Model 0 - Model 2	Model 0 - Model 3	Model 3- Model 4
LRT	---	---	13.0	7.1	11.4	15
df	---	---	5	4	7	13
p-value	---	---	0.023	0.131	0.122	0.307
Total N of persons/groups	---	76	76	76	76	76
Total N of Observations	---	1846	1846	1846	1846	1846

* $p < .05$.

Note. Condition, social and cognitive conditions = 0, physical activity (PA) condition = 1; Vocab = Shipley Vocabulary Scale; Base_PA = baseline physical activity, reported in minutes per day and square root transformed; EMA_PA = geometric mean of ecological momentary assessment of physical activity across 14 days, reported in minutes per day and square root transformed; LRT = Likelihood ratio test; AIC = Akaike Information Criteria.