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Research Article

Historic Cognitive Function Trajectories as Predictors of Sedentary Behavior and Physical Activity in Older Adults

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Abstract

Background: We examined whether trajectories of cognitive function over 10 years predict later-life physical activity (PA), sedentary time (ST), and sleep.

Methods: Participants were from the Adult Changes in Thought (ACT) cohort study. We included 611 ACT participants who wore accelerometers and had 3+ measures of cognition in the 10 years prior to accelerometer wear. The Cognitive Assessment Screening Instrument (CASI) measured cognition and was scored using item-response theory (IRT). activPAL and ActiGraph accelerometers worn over 7 days measured ST and PA outcomes. Self-reported time in bed and sleep quality measured sleep outcomes. Analyses used growth mixture modeling to classify CASI-IRT scores into latent groups and examine associations with PA, ST, and sleep including demographic and health covariates.

Results: Participants (Mean age = 80.3 (6.5) years, 90.3% White, 57.1% female, 29.3% had less than 16 years of education) fell into 3 latent trajectory groups: average stable CASI (56.1%), high stable CASI (34.0%), and declining CASI (9.8%). The declining group had 16 minutes less stepping time (95% confidence interval [95% CI]: 0.6, 31.4), 1 517 fewer steps per day (95% CI: 138, 2 896), and 16.3 minutes per day less moderate-to-vigorous PA (95% CI: 1.3, 31.3) compared to the average stable group. There were no associations between CASI trajectory and sedentary or sleep outcomes.

Conclusions: Declining cognition predicted lower PA providing some evidence of a reverse relationship between PA and cognition in older adults. However, this conclusion is limited by having outcomes at only one time point, a nonrepresentative sample, self-reported sleep outcomes, and using a global cognition measure.

Keywords: Cognitive aging, Exercise, Sedentary time, Sleep

Physical inactivity, sedentary behavior, and sleep make up the 24-hour activity cycle (1). These behaviors have been independently associated with cognitive decline and are predictive of Alzheimer's Disease and Related Dementias (ADRD) in older adulthood (2–14). Given the evidence base, the 2020 Lancet Commission included physical inactivity as one of 12 modifiable risk factors for ADRD and poor sleep is also mentioned as a probable risk factor (2). Importantly, the report notes that "People might stop exercising due to prodromal dementia so inactivity might be either a consequence or a cause or both in dementia and might be more of a risk in those with cardiovascular morbidity" (2). More research is needed to examine whether historical cognition predicts physical activity, sedentary time, and sleep—the components of the 24-hour activity cycle (1).

Several prior studies indicate that changes in cognition, as well as brain structure (15) and volume (16,17), may predict subsequent physical activity (18–21) and sedentary behavior (22) although some studies have not observed bidirectional associations (23,24). We are unaware of studies examining whether changes in cognition affect sleep. A limitation of prior research is that most studies relied on self-reported measures of physical activity and sedentary behavior, which can be imprecise. Untangling the possibility of bidirectional relationships, which could suggest reverse causality, in the association between 24-hour activity cycle behaviors and cognitive decline is critical.

We leveraged data from the Adult Changes in Thought (ACT) epidemiologic cohort study to examine whether historic trajectories of global cognitive function predicted accelerometer-derived physical activity, sedentary behavior, and self-reported sleep duration and quality. We hypothesize that better historical cognition over time (ie, higher scores, better maintenance) is associated with higher physical activity,

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lower sedentary time, and better self-reported sleep duration and quality.

Method

Adult Changes in Thought Cohort

The ACT Study has been ongoing since 1994 and enrolls participants randomly invited from the membership panels of Kaiser Permanente Washington. Eligibility criteria include being 65 years and older and not having a diagnosis of dementia. Participants partake in biennial assessment visits including screening for incident dementia, and they are followed until death, disenrollment, or dementia onset. The original cohort was supplemented with replacement participants beginning in 2000 and in 2005 the decision was made to begin rolling recruitment to hold the study size stable at approximately 2 000 active participants. Participants undergo biennial assessments at a research clinic located in Seattle, WA or, for those unable to visit the clinic, home visits are provided. All procedures are approved by the Kaiser Permanente interregional institutional review board. Beginning in 2016, participants were invited to wear 2 accelerometers as described previously (25). ACT participants were ineligible to wear devices if they were wheelchair bound, undergoing hospice or critical illness care, living in a nursing home, or memory problems that became evident during testing. Participants who successfully wore both accelerometer devices in the first wave of data collection (2016–2018) and had at least 3 prior ACT visits with cognition assessment in the prior 10 years were included in the present analysis.

Exposure Variables

The Cognitive Abilities Screening Instrument (CASI) has been historically collected at each participant's biennial visit for the ACT Study and was used to define trajectories in global cognition over a 10-year look-back period prior to activity and sleep outcome measurement. The CASI is a measure of global cognition including assessment of attention, orientation, memory, visual construction, and verbal fluency. CASI scores range from 0 to 100 with scores less than 86 indicating possible dementia (26). ACT participants with scores below 86 are further evaluated to confirm dementia status and diagnosis. We used item response theory scores for the CASI (CASI-IRT), which utilizes responses to each item to create a score that addresses the limited sensitivity of the CASI for high scorers as well as the nonlinear measurement properties of the scores (27). CASI-IRT scores are generally linear in scale and scores can be considered similar to standard deviation units with the mean being approximately 0 with a standard deviation of 1 (27). In the past 10 years, a maximum of 6 CASI-IRT assessments were possible (ie, first wave timepoint plus5 prior biennial ACT study visits). At least 3 CASI-IRT measurements in that time period were required for inclusion.

Outcome Variables

We measured sedentary behavior and steps with the activPAL3 micro (PAL Technologies, Glasgow, UK) accelerometer. Participants wore the activPAL on the front center of their upper thigh 24 hours a day for 7 days. Prior to device placement, activPALs were sealed in a waterproof casing and adhered with medical tape ensuring the device could be worn while bathing, showering, or swimming. During activPAL wear, participants kept a sleep log indicating their in-bed and out-of-bed times. Devices were fitted at participant biennial visits beginning in April 2016 and they were mailed back to the research team. Data were downloaded using activPAL proprietary software, and "events" files were exported for each participant (28). Data from these "events" files were then processed through an R program that removed in-bed time based on participant self-report. The program generated visual heat maps that were reviewed for quality control purposes, and then summarized into final output variables used in analyses averaged over days the device was worn. Summary variables of interest included mean daily measures of: total steps, sitting time (minutes), standing time (minutes), stepping time (minutes), and mean sitting bout duration (minutes).

Light-intensity and moderate-to-vigorous physical activity were measured with the ActiGraph wGT3X+ (ActiGraph LLC, Pensacola, FL, USA) waist-worn accelerometer, which was worn for 7 days simultaneously with the activPAL. Participants were instructed to remove the ActiGraph when bathing, showering, or swimming and indicated this on the sleep log. ActiGraphs were initialized to record at 30 Hz using ActiLife software (Version 6.13.3). Data were processed using 15-s epochs and the normal filter. The Choi algorithm was used to remove periods of nonwear defined as 90 or more minutes of zero counts per minute by vector magnitude counts (29). Sleep logs were used to determine time in bed. Light-intensity physical activity was defined as vector magnitude counts of 19–518 and moderate-to-vigorous physical activity as >518 per 15-s epoch per the Women's Health Initiative calibration study (30). Summary variables of interest included mean daily measures of light-intensity physical activity (minutes) and moderate-to-vigorous intensity physical activity (minutes). To be included in this analysis, participants were required to have worn the activPAL and ActiGraph for 10 hours or more on 4 or more days. Detailed procedures and processing decisions for all accelerometer data (activPAL and ActiGraph) are described elsewhere (25).

Average daily time in bed (a surrogate for sleep time) was measured by self-reported diaries that participants kept during accelerometer wear. Participants recorded the time they got into bed and out of bed for each day they wore the devices. We also captured self-reported sleep quality with the 8-item PROMIS sleep disturbance scale (31,32) via paper survey administered during the time of participants' accelerometer wear and returned via mail with their device packet. Raw scores were converted to *T* scores and standard error estimates according to PROMIS scoring tables (continuous, higher scores indicate more sleep disturbance and lower quality sleep and have a mean of 50 and standard deviation of 10).

Statistical Analysis

Growth mixture modeling (GMM) of the CASI-IRT score trajectories in the 10 years prior to the physical activity measurement (baseline) was used to classify individuals into latent groups of cognitive function. Adjusted associations between the derived latent cognitive groups and 8 separate behavioral activity outcomes were assessed using multivariable linear regression models adjusted for baseline covariates, as described below. The 8 outcomes of interest were: activPAL-derived steps per day, times sitting, standing, stepping, and average bouts of sitting; ActiGraph light intensity and moderate-vigorous activity; time in bed; and PROMIS score. The activity time measures were analyzed as minutes

per day. For the GMM, we allowed for there to be covariate effects on both the latent class variable and class indicators (CASI-IRT score), following the modeling approach proposed by Vermunt and Magidson (33). This approach can be seen as a modified version of the 3-step latent class modeling approach of Vermunt (34). The work of Asparouhov and Muthén (35) and Janssen et al. (36) demonstrated that ignoring direct effects of covariates on class indicators can otherwise lead to biased inference in the downstream outcome model. We allowed for the potential direct effects of 3 covariates: age, sex, and years of education (Supplementary Figure S1). We briefly described the GMM modeling procedure, with further details provided in Supplementary Appendix S1.

In the first step, GMM was applied to the repeatedly measured CASI-IRT score as class indicators to select the best fitting model with respect to the number of latent groups and which of 3 covariates (age, sex, education), hypothesized to have potential effects on both the latent trajectory groups and the longitudinal CASI-IRT score, should be included in the GMM. This first step involved iterative steps aimed at first selecting the best GMM without any covariates and then selecting the necessary covariates from the a priori list by assessing their associations with the latent groups and the longitudinal CASI-IRT score in this simple GMM model. The final GMM model was the one obtained by refitting with the selected covariates and number of groups selected by the simple GMM model. In the second step, each subject was assigned to a CASI-IRT trajectory group with the highest posterior probability estimated by the final GMM (ie, using modal assignment). In the third step, the associations between identified latent cognitive groups and the physical activity outcomes were estimated using the improved Bolck, Croons, and Hagenaars method (34), which accounts for the uncertainty in the group membership assignments. In this third step, the outcome model also included the following covariates: self-reported age at device wear (from electronic health records), sex (male, female) at study entry, body mass index (BMI) at device wear, living arrangement (alone vs with others) at device wear, education (16 years or more vs less than 16 years) at entry to the study, work and retirement status (retired vs working full/part/other time) at device wear, depressive symptoms (Center for Epidemiologic Studies Depression scale, CES-D (37), continuous score) at device wear, self-rated health (fair/poor vs good/excellent) at device wear, and accelerometer awake wear time (excluding participant-reported time in bed) for the ActiGraph and activPAL outcomes.

Statistical testing was done at the 0.05 alpha level. Descriptive statistics were performed in R software version 4.2.2 (38), and GMM analyses were performed using Latent GOLD version 6.0 (39). Latent GOLD Syntax for performing the entire GMM analysis is provided on GitHub (https://github.com/yinxiangwu/cognitive-trajectory-LG-analysis).

Results

Participant Characteristics

Within the ACT activity monitoring subsample, 951 participants wore both the ActiGraph and activPAL and had valid data. Of these, 611 had at least 3 valid CASI scores within 10 years prior to device wear and were included in the analysis (see Figure 1). The analytic sample was slightly older, had better cognition, and better physical function than ACT cohort participants who were eligible to wear devices, but were similar in other characteristics such as sex and education level (see Table 1, Supplementary Table S1). Participants in the analytic cohort had a mean age of 80.3 years (*SD* = 6.5 years, range = [69, 100] years), 57.1% were female, 90.3% were White, 70.7% had 16 years or more of education, 91.8% reported good to excellent self-rated health, and 71.5% had no difficulty walking half a mile.

Trajectory Modeling

In the first step of GMM, the likelihood ratio test for comparing linear and cubic polynomial trajectories had a p value > 0.05, indicating linear trajectories would be adequate. We considered linear trajectories with random intercepts and slopes when fitting further GMMs. The 3-class solution was identified as having the best fit considering the goodness of fit statistics (Supplementary Table S2), classification accuracy (Supplementary Table S3), sample sizes identified in the classes, and apparent clinical relevance of the differences in the identified groups (40). The 4-class solution did have statistical evidence of improved goodness of fit by the Lo-Mendell-Rubin likelihood ratio (LMR) test (41); however, it did not seem to identify groups with clear distinguishing features and had high classification errors (see Supplementary Table S4). Age was identified as a covariate having direct effects on both the latent class membership and CASI-IRT trajectories and included in the final GMM. According to modal assignment by this final GMM, there were 343 (56.1%) of participants in class 1, referred to as the "average stable CASI" category; this group had CASI scores that were at average levels for the group and that did not change over time. Class 2 consisted of 208 (34.0%) participants, labeled "high stable CASI" meaning that their CASI scores were higher than the "average stable CASI" group and their scores stayed high over time. Class 3 included 60 (9.8%) participants labeled "declining CASI"; this group started with CASI scores at varying levels but the score declined over time, with an average decline of about 1 *SD* over 10 years. Figure 2 and Supplementary Figure S2 depict the predicted and observed trajectories, respectively, for individuals by identified class.

Table 2 provides descriptive statistics for the participants in the analytic cohort by assigned class membership. Using the average stable CASI group as the reference, the high stable CASI group had a larger proportion of participants aged 65–74 and appeared to be more likely to be female, have more years of education, have lower BMI, and have better self-rated health. There were no notable differences apparent between the physical activity outcomes for the high stable group and the average stable group. In contrast, compared to the average stable CASI group, the small declining CASI group appeared to have a larger proportion of participants that were aged 85 or older, had fewer years of education, had more difficulty walking half a mile, and had worse self-rated health. At the time of device measurement, the declining CASI group had on average more sitting time, less standing, stepping, and moderate-to-vigorous activity time, with many fewer steps. It should be noted that the above comparisons were merely based on the unadjusted descriptive statistics calculated for the classes based on modal assignment, which does not account for the uncertainty in class membership assignments.

Activity Outcome Modeling

Table 3 presents the GMM results estimating the associations of trajectory group membership with physical activity and

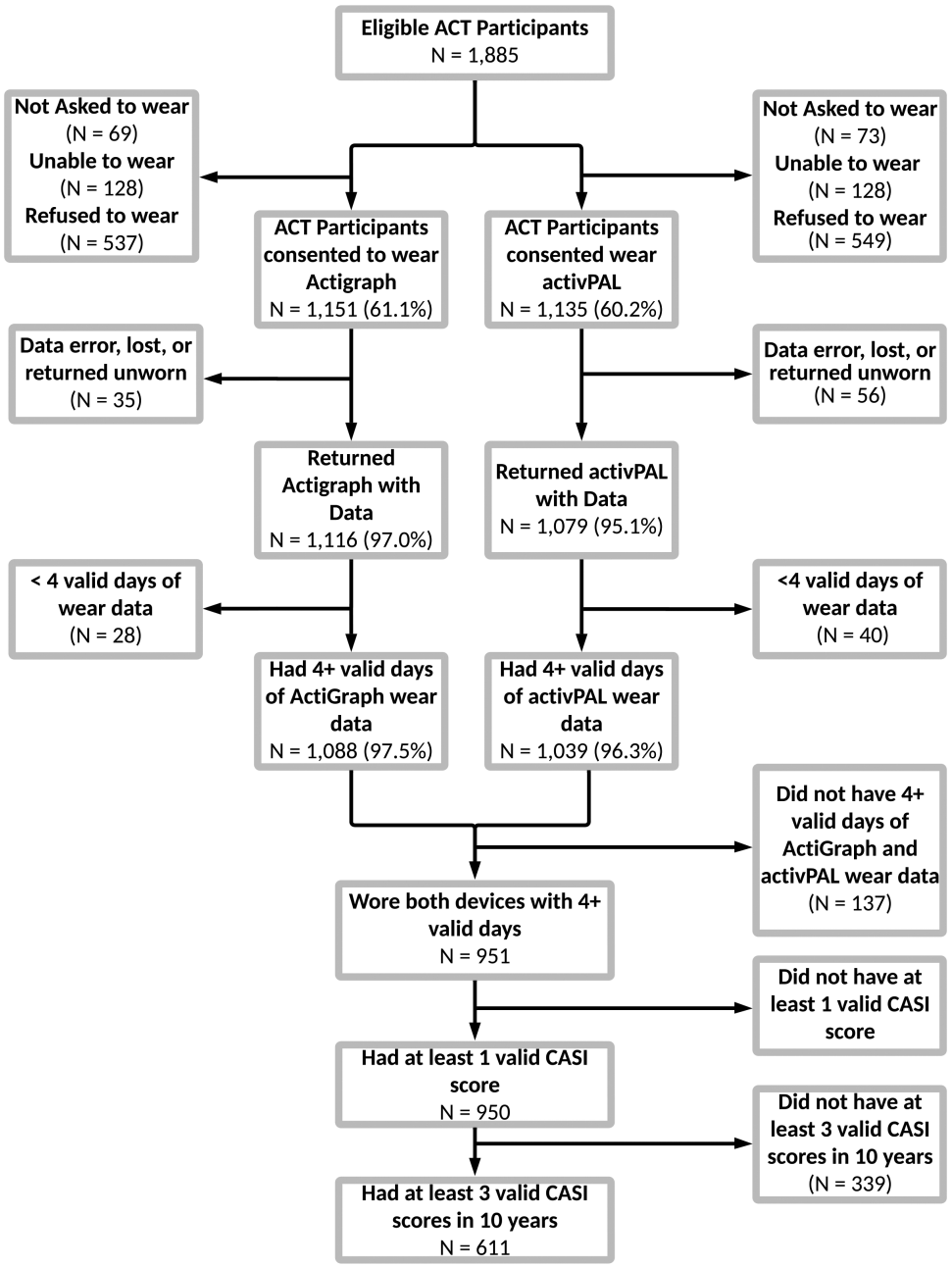

Figure 1. Analytic sample flow diagram.

sleep outcomes, corrected for the uncertainty in the latent group membership. Compared to the average stable CASI group, the declining group had less activPAL stepping time by an estimate (95% confidence interval, CI) of 16 (0.6, 31.4) minutes per day, 1 517 (138, 2 896) fewer steps, and 16.3 (1.3, 31.3) fewer minutes per day of MVPA according to ActiGraph. The other outcomes of interest, including time in bed and sleep quality, showed nonsignificant differences. Comparing the high stable CASI and average stable CASI groups, we observed nonsignificant differences for all the outcomes. The results we summarized here were confirmed by the sensitivity analysis, where the age effect was modeled as a cubic polynomial in all step-3 regression models (see Supplementary Table S4). Supplementary Tables S5–S13 display the full results for all models.

Discussion

Overall, we observed fairly stable levels of cognition on a screener of cognitive status over 10 years in the ACT cohort. Those with prior declining cognition had lower later-life physical activity levels compared to those with stable cognition. We did not observe differences in physical activity between the high stable and average stable cognitive function groups, indicating that, regardless of where cognitive function starts at older ages, maintaining that level of function is most impactful for physical activity engagement. In other words, higher levels of cognitive resources are not required for participation in physical activity as long as one's level of function is sustained over older adulthood. The declining group had decreases that likely represent nonnormal cognitive aging given that the decrease was about 1 *SD* over the exposure

Table 1. Sample Characteristics in the Adult Changes in Thought Cohort Overall, Those Eligible for the Analysis, and the Final Analytic Cohort*

	Invited ACT Cohort	Activity Monitor ACT Cohort	Available in This Analysis	Excluded From Analysis
	N = 1 885	*N* = 950	*N* = 611	(*N* = 339)
Age (years) Category, *n* (%)				
65–74	644 (34.2%)	398 (41.9%)	151 (24.7%)	247 (72.9%)
74–84	759 (40.3%)	399 (42.0%)	316 (51.7%)	83 (24.5%)
85+	482 (25.6%)	153 (16.1%)	144 (23.6%)	9 (2.7%)
Age (years)				
Mean (*SD*)	79.5 (7.8)	77.7 (7.0)	80.3 (6.5)	73.0 (5.0)
Gender, *n* (%)				
Female	1 094 (58.0%)	529 (55.7%)	349 (57.1%)	180 (53.1%)
Male	791 (42.0%)	421 (44.3%)	262 (42.9%)	159 (46.9%)
Race, *n* (%)				
American Indian or Alaskan Native	2 (0.1%)	—	—	—
Asian	71 (3.8%)	28 (3.0%)	20 (3.3%)	8 (2.4%)
Black	42 (2.2%)	15 (1.6%)	13 (2.1%)	2 (0.6%)
Native Hawaiian or Pacific Islander	2 (0.1%)	2 (0.2%)	—	2 (0.6%)
White	1 673 (89.0%)	861 (90.7%)	552 (90.3%)	309 (91.4%)
Other or mixed	89 (4.7%)	43 (4.5%)	26 (4.3%)	17 (5.0%)
Latino/Hispanic Ethnicity, *n* (%)				
Yes	32 (1.7%)	12 (1.3%)	9 (1.5%)	3 (0.9%)
No	1 846 (98.3%)	935 (98.7%)	600 (98.5%)	335 (99.1%)
Currently work for pay, *n* (%)	285 (15.1%)	178 (18.7%)	88 (14.4%)	90 (26.5%)
Education level 16+ years, *n* (%)	1 323 (70.2%)	710 (74.7%)	432 (70.7%)	278 (82.0%)
BMI, Mean (*SD*)	27.0 (5.2)	26.9 (5.0)	26.7 (4.6)	27.3 (5.0)
Depressive symptoms (CES-D), Mean (*SD*)	3.6 (4.2)	3.5 (3.9)	3.57 (3.8)	3.5 (3.9)
CES-D_score ≥ 10, *n* (%)	179 (9.7%)	82 (8.7%)	50 (8.3%)	32 (9.6%)
activPAL wear time, Mean (*SD*)	—	928.9 (63.4)	924.9 (64.4)	936.1 (61.0)
Actigraph wear time, Mean (*SD*)	—	912.6 (65.7)	909.1 (66.2)	918.8 (64.4)
Current CASI-IRT, Mean (*SD*)	0.4 (0.8)	0.6 (0.7)	0.6 (0.7)	0.7 (0.6)
Self-reported difficulty walking half mile, *n* (%)				
Able to walk half mile	1 237 (66.1%)	722 (76.0%)	435 (71.2%)	287 (84.7%)
At least some difficulty walking half mile	624 (33.3%)	225 (23.7%)	173 (28.3%)	52 (15.3%)
Don't know/refused	11 (0.6%)	3 (0.3%)	3 (0.5%)	—
Live alone, *n* (%)	729 (38.7%)	325 (34.2%)	227 (37.2%)	98 (28.9%)

Notes: BMI = body mass index; CASI-IRT = Cognitive Abilities Screening Instrument scored with item response theory; CES-D = Center for Epidemiologic Studies Depression scale.
*Invited ACT cohort (*N* = 1 885) missing values: race = 6, Hispanic ethnicity = 7, NDI = 3, currently work for pay = 3, BMI = 95, CES-D: = 43, CASI-IRT score = 8, difficulty walking half mile = 13, living arrangement = 3; ACT activity monitoring cohort (*N* = 950) missing values: race = 1, Hispanic ethnicity = 3, BMI = 19, CES-D = 9, CASI-IRT score = 3; available in this analysis (*N* = 611) missing values: Hispanic ethnicity = 2, BMI = 16, CES-D = 5, CASI-IRT score = 3.

period. These findings lend support to research suggesting that there could be bidirectional associations between physical activity and later life cognitive decline (20,21). We did not see any effect of the global cognition trajectory groups on sedentary behaviors, time in bed, or light-intensity physical activity.

Our findings confirm prior studies that demonstrated worse cognitive function is associated with lower physical activity. Using 6 years of follow-up data from the English Longitudinal Study on Aging, researchers identified that reductions in executive function predicted reduced physical activity with a magnitude that was 50% stronger than the effect of PA on cognition (20). Another study found that cognitive decline preceded declines in physical activity in a sample of more than 50 000 adults older than 50 years (21). The authors suggested that cognitive effort is required for overcoming innate tendencies toward physical inactivity and that once cognitive resources are lessened, it is more difficult to overcome this tendency (21). Further, executive function, which involves the ability to plan, problem-solve, and engage in effortful behaviors such as physical activity, is crucial for being able to carry out conscious intentions and plans for engaging in physical activities at higher intensity (20). In adults older than 50 years in the Survey of Health, Ageing, and Retirement in Europe cohort, there were bidirectional associations between performance on a task of delayed recall and self-reported physical activity measured 2 years apart (21). In this study, physical activity was a stronger mediator of the relationship between

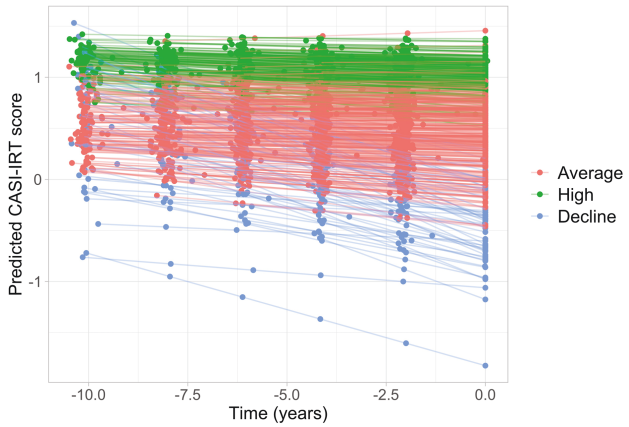

Figure 2. Predicted CASI-IRT scores in the sample ($N = 611$). Each dotted curve in the figure corresponds to the predicted CASI-IRT score for a specific subject, computed based on the final fitted growth mixture model (GMM). The horizontal axis represents years prior to the baseline (time = 0). For example, −10 means 10 years prior to the baseline. Subjects were assigned to 1 of the 3 classes based on modal assignment.

delayed recall performance and depressive symptoms compared to models with cognitive function as a mediator of the relationship between physical activity and depressive symptoms. The conclusion was that "higher cognitive resources favor the engagement in physical activity, which contributes to reduced depressive symptoms" (21). With the addition of the current findings, there is coalescing evidence that some of the association between physical activity and cognition may be bidirectional in nature.

We did not see that cognition trajectories predicted sedentary behavior measures. Associations could be obfuscated in part because the type of sedentary behavior may be important to consider rather than the total amount of time spent sitting. Our findings cannot determine whether cognition predicts specific types of sedentary behavior, such as television viewing, reading, and computer use, which all require varying levels of cognitive effort (42). The type of sedentary behavior itself could change with cognitive aging, for example, people might shift time spent reading time to television as cognition declines, which future research could further examine.

Table 2. Descriptive Characteristics of Participants by Identified Cognitive Trajectory Class

		Class According to Modal Assignment		
	Overall	Average Stable Cognition	High Stable Cognition	Declining Cognition
N, (%)	611	343 (56.1%)	208 (34.0%)	60 (9.8%)
Age in years, mean (*SD*)	80.3 (6.5)	78.9 (5.2)	79.8 (7.0)	89.4 (4.5)
Age categories in years				
65–74	151 (24.7)	80 (23.3)	71 (34.1)	0 (0.0)
75–79	171 (28.0)	127 (37.0)	44 (21.2)	0 (0.0)
80–84	145 (23.7)	99 (28.9)	38 (18.3)	8 (13.3)
85+	144 (23.6)	37 (10.8)	55 (26.4)	52 (86.7)
Gender				
Male	262 (42.9)	167 (48.7)	65 (31.2)	30 (50.0)
Female	349 (57.1)	176 (51.3)	143 (68.8)	30 (50.0)
Education				
16+ years	432 (70.7)	233 (67.9)	166 (79.8)	33 (55.0)
<16 years	179 (29.3)	110 (32.1)	42 (20.2)	27 (45.0)
Able to walk half mile[*,‡]	435 (71.5)	252 (73.9)	161 (77.4)	22 (37.3)
Not working for pay	523 (85.6)	280 (81.6)	186 (89.4)	57 (95.0)
Living alone	227 (37.2)	119 (34.7)	82 (39.4)	26 (43.3)
Self-rated health fair/poor[†], mean (*SD*)	50 (8.2)	28 (8.2)	9 (4.3)	13 (21.7)
BMI[‡] (kg/m^2)	26.70 (4.65)	27.34 (4.63)	26.05 (4.61)	25.29 (4.30)
CES-D score[‡]	3.57 (3.84)	3.37 (3.78)	3.77 (3.74)	4.07 (4.46)
activPAL sitting min/day	602.94 (119.62)	601.29 (117.24)	596.12 (121.89)	636.04 (121.82)
activPAL standing min/day	239.75 (99.84)	240.02 (96.40)	245.13 (99.59)	219.52 (117.82)
activPAL stepping min/day	82.25 (38.12)	85.02 (37.72)	85.66 (38.18)	54.59 (28.34)
activPAL steps/day	6 354.56 (3 409.21)	6 569.15 (3 408.22)	6 697.17 (3 423.14)	3 940.15 (2 260.96)
activPAL bout duration	16.05 (7.99)	16.04 (7.48)	15.36 (7.96)	18.45 (10.31)
ActiGraph LPA min/day	276.48 (77.81)	277.55 (77.76)	279.30 (75.89)	260.52 (83.94)
ActiGraph MVPA min/day	61.29 (42.60)	64.32 (40.87)	66.49 (45.23)	25.90 (21.94)
Time in bed min/day	516.06 (65.74)	514.73 (68.38)	513.68 (58.40)	531.95 (72.96)
PROMIS score[‡]	46.51 (7.90)	46.39 (7.91)	46.48 (7.46)	47.27 (9.40)

Notes: BMI = body mass index; CES-D = Center for Epidemiologic Studies Depression scale; LPA = light physical activity; MVPA = moderate-to-vigorous physical activity; PROMIS = Patient-Reported Outcomes Measurement Information System.
[*]Compared to some or greater difficulty walking.
[†]Compared to excellent/very good/good.
[‡]Missing values: BMI $n = 16$; CES-D score $n = 5$; ability to walk half a mile $n = 3$; PROMIS Score $n = 54$.

Table 3. Associations of Latent CASI-IRT Trajectory Group With Physical Activity and Sleep Behavior Outcomes*

Outcome	Class	Est	95% CI†	*p* Value†
AP sit time (min/day)	Average	Ref	—	—
	High	15.5	(−18.8, 49.7)	.38
	Decline	14.3	(−46.9, 75.5)	.65
AP stand time (min/day)	Average	Ref	—	—
	High	−11.9	(−41.2, 17.4)	.43
	Decline	1.7	(−52.4, 55.7)	.95
AP step time (min/day)	Average	Ref	—	—
	High	−3.6	(−13.6, 6.5)	.49
	Decline	−16.0	(−31.4, −0.6)	.042
AP num steps (count/day)	Average	Ref	—	—
	High	−270.5	(−1 187.8, 646.8)	.56
	Decline	−1 517.0	(−2 895.7, −138.3)	.031
AP bout duration (min/day)	Average	Ref	—	—
	High	−0.4	(−2.4, 1.6)	.68
	Decline	0.3	(−4.2, 4.8)	.89
AG light activity (min/day)	Average	Ref	—	—
	High	−17.2	(−37.9, 3.4)	.1
	Decline	−5.0	(−38.1, 28.1)	.77
AG moderate-to-vigorous activity (min/day)	Average	Ref	—	—
	High	1.6	(−9.9, 13.1)	.78
	Decline	−16.3	(−31.3, −1.3)	.033
Time in bed (min/day)	Average	Ref	—	—
	High	−4.5	(−24.0, 15.1)	.66
	Decline	−5.5	(−43.3, 32.3)	.78
PROMIS Sleep Disturbance Score	Average	Ref	—	—
	High	0.1	(−2.3, 2.5)	.93
	Decline	−2.0	(−6.1, 2.2)	.35

Notes: AG = ActiGraph; AP = activPAL; BMI = body mass index; CES-D = Center for Epidemiologic Studies Depression scale; CI = confidence interval; Est = estimate of regression coefficient; LPA = light physical activity; MVPA = moderate-to-vigorous physical activity.
*Analysis adjusted for age, gender, education, BMI, CES-D scores, self-report health, retirement, live alone, AG/AP awake wear time (for AP/AG outcomes). When PROMIS Score was the outcome, $N = 540$‡; for the other outcomes, $N = 590$‡.
†95% CIs and *p* values were calculated based on normal approximation using estimated robust standard errors.
‡Observations with missing data on the outcome and covariates were excluded from the analysis.

Further, we did not see that cognitive trajectories predicted self-reported sleep quality or duration. People in our sample had generally high levels of sleep quality. We did not have important device-based measures of sleep patterns such as sleep efficiency or wake after sleep onset. Research to-date has focused on associations between sleep patterns and future cognitive changes (7–9) and not the opposite direction. It is known that people with dementia have more frequent sleep disruption (43) so there is a need for future research to examine whether there are bidirectional associations and to leverage device-based assessments of sleep, which were not available in our sample.

Limitations for the current study include reliance on a global cognition screener, where most participants score at higher values in the ACT sample that wore accelerometers. This was the only cognition measure regularly available during the study period; future studies should examine multiple cognitive domains. We had device measurement of physical activity at only a single point in time at the end of the trajectory period, so we cannot address how physical activity changed over that period or whether lower levels of physical activity in the declining trajectory group were also lower at the beginning of the look-back period. Our measure of sleep was limited to self-reported time in bed and self-reported sleep quality rather than an objective measure of sleep. The ACT sample is not fully representative of the population of King County, WA, as it is more highly educated and primarily White (44). Because the sample was 90% non-Hispanic White, we could not include race or ethnicity as a covariate and proxy of exposure to systemic inequities. Analyses are of observational data and thus we cannot rule out the possibility of residual confounding. We did not have information on musculoskeletal conditions and mobility among participants though we were able to include BMI and self-rated health. Finally, associations were not adjusted for multiple comparisons and thus are considered weak evidence that should be confirmed by future studies. Strengths include a focus on the oldest age group, with nearly 25% over age 85. Our analyses accounted for potential misclassification of latent trajectory classifications, as well as accounted for potential direct effects of external covariates on the latent classes. Results were robust across multiple sensitivity analyses that varied modeling assumptions.

Conclusion

Older adults with steeper declines in cognition over a 10-year period had lower physical activity levels. This provides some evidence that there may be bidirectional associations between physical activity and cognition. We also found no relationships between cognitive trajectory group and sedentary behavior, time in bed, or sleep quality. Future studies can further examine whether there are bidirectional associations between the 24-hour activity cycle—physical activity, sedentary behavior, and sleep—and cognition measures, which include a variety of cognitive domains.

Supplementary Material

Supplementary data are available at *The Journals of Gerontology, Series A: Biological Sciences and Medical Sciences* online.

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Conflict of Interest

None.

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Author Contributions

D.E.R.: funding, conceptualization, project administration, led drafting, reviewed, and edited the manuscript. Y.W.: data curation, analysis, methodology, drafted, reviewed, and edited the manuscript. A.I.: data curation, analysis, methodology, reviewed, and edited the manuscript. M.A.G.-H.: conceptualization, methodology, project administration, reviewed, and edited the manuscript. S.-M.: funding, conceptualization, project administration, methodology, reviewed, and edited the manuscript. A.Z.L.: conceptualization, funding, methodology, reviewed, and edited the manuscript. P.A.S.: data curation, analysis, methodology, drafted, reviewed, and edited the manuscript.

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