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24-hour movement behaviours are cross-sectionally associated with cognitive function in healthy adults aged 55 years and older

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Global life expectancy has consistently increased since 1950, resulting in more people living to an older age. However, maintaining optimal cognitive health is a challenge as ageing is accompanied by natural cognitive decline, which can affect daily functioning and quality of life. Importantly, modifiable lifestyle factors can play a role in promoting healthy ageing. Among these, physical activity (PA), sedentary behaviour (SB) and sleep have gained increasing attention for their potential contributions to cognitive health. This study investigates in greater detail how these 24-hour movement behaviours relate to cognitive function in older adults. Participants were 233 healthy adults aged 55 years and older (51.1% women; mean age 68.3 ± 7.7 years). Daily time spent in light PA (LPA), moderate-to-vigorous PA (MVPA), SB and sleep was derived from 7-day wrist-worn ActiGraphy (wGT3X-BT). Cognitive function, including short-term and long-term memory (STM, LTM), executive function (EF) and processing speed, was assessed using the Cambridge Neuropsychological Test Automated Battery (CANTAB) and expressed in z-scores. Compositional multiple linear regression was used to assess the association between time use and cognitive function. Compositional isotemporal substitution examined how hypothetical time reallocations between the different movement behaviours were related to cognitive function. Even after adjusting for age, sex, educational level, social isolation and multiple testing, time use was significantly associated with short-term memory ($p = 0.01$) and executive function ($p = 0.001$). Hypothetical time reallocations of 30-min from LPA to MVPA were associated with the largest significant mean differences of 0.19 [95% confidence interval 0.05–0.32] in STM z-scores and 0.21 [0.10–0.33] in EF z-scores. Notably, reallocating time from LPA or sleep to SB was also related to better EF z-scores. Importantly, reallocating even 5 minutes away from MVPA to any other behaviour was significantly associated with poorer z-scores in STM and EF. No significant associations were observed for long-term memory and processing speed. This study underscores the importance of considering 24-hour movement behaviours in cognitive health at older age. Dedicating time to moderate-to-vigorous PA seems to be important for specific cognitive domains. Longitudinal studies are needed to further explore these relationships, with a focus on detailed assessments of the various contexts in which PA and SB occur.

Keywords Physical activity, Sedentary behaviour, Sleep, Cognition, Ageing, Compositional data analysis

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Background

Life expectancy has consistently increased since 1950 and is projected to continue doing so for the next decades[1]. Consequently, the number and proportion of older adults in the population is rapidly growing, leading to a demographic shift which presents new economical and societal challenges[2,3]. Moreover, ageing is characterized by the onset of several health issues, with chronic diseases and disabilities becoming increasingly prevalent among older adults[4,5]. Therefore, the United Nations (UN) declared this current decade (2021–2030) as the UN Decade of Healthy Ageing, making it a global priority to focus on successful ageing[6]. One important aspect of this is maintaining optimal cognitive health at older age[7,8]. After all, ageing is accompanied by a natural cognitive decline which affects people's daily functioning and, if it develops to dementia, their ability to live independently[9]. Especially fluid cognitive abilities, such as memory, executive functioning and processing speed, seem to be more negatively affected by age[10].

Several modifiable lifestyle factors, such as alcohol intake and smoking, but also physical activity, impact the trajectory of cognitive ageing[11,12]. Physical activity (PA) is neuroprotective and associated with better cognitive performance in older adults[13–15]. Moreover, high and even low-to-moderate PA levels seem to significantly protect older adults against cognitive decline and cognitive impairment by reducing their relative risk by 38% and 35%, respectively[16]. General cognition, memory and executive functioning, including processing speed, benefit in particular[17,18]. Therefore, the World Health Organization (WHO) issued a strong evidence-based recommendation for PA as a strategy to reduce the risk of cognitive decline in adults with normal cognition[19].

Sedentary behaviour (SB), defined by Tremblay et al.[20] as any waking activity characterized by low energy expenditure while sitting, reclining, or lying down, is also considered a modifiable lifestyle factor linked to cognitive ageing[21]. Negative associations have been reported, linking self-reported SB to impaired general cognition, memory and executive function[22]. Similarly, the review of Rojer et al.[15] identified a modest, but significant, negative association between device-measured SB and general cognition (median [Interquartile Range], $\beta = 0.078$ [0.004–0.184]). In contrast, reviews of Maasakkers et al.[23] and Olanrewaju et al.[24] observed no consistent association between total sedentary time and cognitive outcomes, underscoring the need for further research to elucidate this relationship.

Furthermore, sleep plays a crucial role in maintaining optimal cognitive function in all age groups, including older adults[25]. However, age-related changes in sleep, such as shifts in sleep duration, are negatively associated with cognitive functioning[26]. For example, a meta-analysis on self-reported sleep durations found that older adults who reported either relatively short or long sleep durations had higher odds of poorer cognitive performance on multiple cognitive domains – 40% higher for short sleepers and 58% higher for long sleepers[27]. This inverted U-shape relationship was also identified by Qiu et al.[28]; however their analysis only reported on general cognitive function.

As time is finite during the day, time spent in light PA (LPA), moderate-to-vigorous PA (MVPA), SB and sleep are co-dependent. Spending more time in MVPA, for example, necessitates reducing time spent in other behaviours. Therefore, the role of these behaviours for health outcomes such as cognition should not be studied in isolation, but within a 24-hour compositional framework[29]. This framework furthermore allows the investigation of hypothetical time substitutions between the different time-use behaviours and their impact on health outcomes[30]. In other words, it becomes possible to predict differences in health outcomes when redistributing time (e.g. 5 to 30 minutes) from one behaviour to another (e.g. from SB to PA). This approach has recently gained increasing attention in public health promotion[31] and has already been incorporated into 24-hour movement guidelines for general health[32,33]. Regarding cognitive health, only a few studies have used this compositional approach to explore the relationship between 24-hour movement behaviours and cognitive outcomes in older adults. Findings remain limited and mixed: some research suggests that reallocating time – either proportionally reallocated from all other time-use behaviours, or specifically taken away from SB, LPA or sleep – to MVPA may have the most beneficial relationship with cognitive outcomes[34,35]. In contrast, others have failed to find any association between time use and cognition in healthy older adults[36,37]. Notably, among the latter studies, only Dumuid et al.[35] and Mellow et al.[37] exclusively utilized device-based measures to assess time use, while the other studies combined self-reported methods with accelerometery to capture the complete 24-hour time-use profile.

Therefore, the present study aims to provide an in-depth analysis of the relationship between 24-hour movement behaviours and cognitive function in community-dwelling adults aged 55 years and above, using innovative statistical methods to further elucidate the associations of time reallocation between behaviours and cognition. Time in LPA, MVPA, SB and sleep will be measured with an accelerometer, while several domains of cognition will be assessed, including short- and long-term memory, executive function and processing speed.

Methods

Study design

The present study is part of the PASOCA-study *(how **P**hysical **A**ctivity and **S**leep relate to **O**ptimal **C**ognitive **A**geing)*, a longitudinal, observational study investigating 24-hour movement behaviours and cognitive function of healthy adults aged 55+ years living in Flanders, Belgium. Informed consent was obtained from all subjects prior to their participation in the study. The study adhered to the principles outlined in the Declaration of Helsinki, was approved by the Ethical Committee Research KU/UZ Leuven (S65167) and is registered at clinicaltrials.gov (NCT05455229). The current research article is based on baseline data, collected between July 2021 and March 2022. The data reported in this manuscript were collected at the home of participants or during university campus visits. They include the questionnaires administered during the first visit of this larger protocol, the accelerometer data collected during the 7 days between this first visit and the second visit that

captured the averaged 24-hour movement behaviours at baseline, as well as the data related to the cognitive test battery administered during the second visit on day 8.

Study population

Healthy, independently living adults aged 55 years and above were recruited through a convenience sampling approach. This age range was selected based on evidence that cognitive decline is already apparent in middle age[38]. Exclusion criteria were assessed through self-report and were based on conditions potentially associated with cognition (a-g) and 24-hour movement behaviours (h-j). These included having (a) a neurodegenerative disease such as Parkinson's, Alzheimer's, multiple sclerosis (MS); or (b) a psychiatric illness such as bipolar disorder, obsessive-compulsive disorder (OCD); or (c) a serious brain injury within the past year or in prior years, with lasting effects; or (d) a stroke; or (e) an acute depressive episode at the time of measurement; or (f) a history of addiction or excessive alcohol abuse; or (g) a first-degree relative diagnosed with dementia; or using (h) a sleeping device (for diagnosed sleep apnoea); or being (i) diagnosed with chronic insomnia; or suffering (j) from severe limitations in performing daily activities. In addition, the Montreal Cognitive Assessment (MoCA) was conducted prior to participation and a score equal to or less than 23 led to exclusion as this might indicate mild cognitive impairment (MCI)[39,40].

Measurements

Sociodemographic and health characteristics

A sociodemographic and health questionnaire was administered and included participants' date of birth, sex (*male/female*), educational level (*highest degree*), living arrangement (*alone/together with a partner*, *family*, *friends*), weight and length (to calculate Body Mass Index (BMI)), alcohol consumption (*never/occasionally/weekly/daily*), smoking habits (*never smoked/ex-smoker/current smoker*), hearing impairment (*no/mild-severe complaints*) and total number of prescribed medications. Educational attainment was assessed according to the International Standard Classification of Education (ISCE) and grouped into three levels, namely low educated (ISCE 0–2), medium educated (ISCE 3–4) and highly educated (ISCE 5–8)[41]. Next, BMI was categorised into three groups: 'healthy' (18.5–24.9 kg/m^2), 'overweight' (25–29.9 kg/m^2) and 'obese' (≥ 30 kg/m^2)[42].

The aforementioned factors were identified in recent literature as factors associated with cognitive function and were therefore included as covariates in the statistical analyses to account for potential confounds. Specifically, *age* was included as covariate as older age is associated with lower cognitive functioning due to age-related neurodegenerative processes that affect memory and executive functions[10]. *Sex* differences in cognitive ageing are also well-documented, showing that men and women may experience cognitive decline differently[43]. *Education level* is a key determinant of cognitive health, with higher education in early life resulting in better cognitive performance in later life[44]. In terms of social factors, *living arrangement* (i.e. cohabitation) served as a proxy for social isolation, which is associated with poorer cognitive outcomes[45,46]. *BMI*, along with health behaviours such as *smoking* and *alcohol consumption*, has been shown to negatively impact brain health[47–49]. *Hearing impairment* is positively associated with accelerated cognitive decline[50]. Finally, Total number of prescribed *medications* served as a proxy for comorbidity and polypharmacy, both of which are negatively associated with cognitive function[51,52].

Device-based measurement of 24-hour movement behaviours (physical activity, sedentary behaviour and sleep)

The 24-hour movement behaviours were measured using a wrist-worn, tri-axial accelerometer (ActiGraph wGT3X-BT), initialized at a sampling frequency of 100 Hz, with the idle sleep mode disabled. Participants were instructed to wear the device continuously on their non-dominant hand for seven full days, only removing it for water-based activities such as showering and swimming. They were also given a diary to record any non-wear, as well as their sleep times, namely time in bed (with the intention to sleep), time asleep (estimation), final wake-up time and time out of bed.

Raw accelerometery data files were downloaded using ActiLife software (version 6.13.4) (ActiGraph, Pensacola, Florida, US) in .gt3x format and further processed in R (version 4.4.1) and RStudio (version 2024.09.1) using the GGIR-package (version 3.1–4)[53,54]. Each file underwent an autocalibration process, in which nonmovement periods were compared to the gravitational acceleration (1*g*) to adjust for potential calibration errors[55]. GGIR's '2023' non-wear detection algorithm assessed the standard deviation and range of acceleration of the raw signals over 60-minute windows, with windows shifting every 15 minutes. A period was classified as non-wear if these criteria (i.e. 13.0 m*g* for standard deviation and 50 m*g* for range) were met in at least two of the three axes. These periods were then imputed using the average values from the same time on other days with valid data.

Next, the acceleration metric ENMO (Euclidean Norm Minus One with negative values rounded to zero) was calculated and summarised over a 5-second epoch. To identify sleep, periods for which the z-angle remained within a 5-degree range for at least 5 minutes were marked as sustained inactivity bouts (SIBs). Guiders from the sleep diary, specifically time in bed and wake-up time, helped to outline the Sleep Period Time (SPT) (i.e. sleep onset to final wake-up) from these SIBs[56]. If accurate sleep detection was lacking (i.e. discrepancies of one hour or more between the algorithm-determined and self-reported sleep onset and wake-up times), alternative guiders were applied – either from the HDCZA algorithm[57] or from participants' recorded out of bed times – whenever these provided more accurate SPT estimates (i.e. closer to participant's reported sleep/wake time and visually more aligned with the signal). A day was defined from midnight to midnight and considered valid if it contained at least 23 hours of recorded data, of which 16 valid hours and at least 2/3 valid waking hours. Each measurement required a minimum of four valid weekdays and one valid weekend day. Ultimately, weighted averages were applied to ensure a consistent 5:2 ratio (i.e. weekday:weekendday) across all files.

To categorize the different activity intensities, cut-points established by Hildebrand et al.[58] and Hildebrand et al.[59] were applied. Sedentary behaviour was defined as acceleration below 44.8 m*g*, light PA between 44.8 m*g* and

100.6 m*g* and moderate-to-vigorous PA as any epoch with acceleration values exceeding 100.6 m*g*. A complete overview of all arguments specified in the GGIR code can be found on GitHub (https://github.com/pjmarent/PASOCAcrosssectional.git).

Cognitive function

Cognitive function was assessed using the Cambridge Neuropsychological Test Automated Battery (CANTAB) on an iPad. CANTAB is a computerised neuropsychological test battery tool designed to measure different cognitive domains[60,61]. The test battery used in PASOCA included six assessments: Delayed Match to Sample (DMS), Verbal Recognition Memory: Immediate and Delayed recall (VRM), One Touch Stockings of Cambridge (OTS), Spatial Working Memory (SWM), Paired Associates Learning (PAL) and Multitasking Test (MTT). A full description of each test can be found in Supplementary Table 1A. The participants completed these tests in a fixed order with the total cognitive test duration being approximately one hour, including one familiarization test (Motor Screening Task) and a 5-minute break. The fixed sequence was developed in consultation with CANTAB's scientific team and structured to alternate between cognitive domains as best as possible to minimize fatigue and carry-over effects. Additionally, the sequence had to accommodate the delayed recall requirement of the VRM, which necessitated a minimum 20-minute interval between initial presentation and recall.

The Cattell-Horn-Carroll-Miyake (CHC-M) cognitive domain taxonomy framework was applied to inform the selection of each test's specific outcome measures[62], along with the recommendations of the researchers from CANTAB and earlier studies using the same tests in a similar population[37,63]. Composite scores were calculated for short-term memory (STM), long-term memory (LTM), executive functioning (EF) and processing speed (PS). In short, mathematical transformations were applied to ensure that higher scores reflected better cognitive performance. Standardized z-scores were then calculated and averaged to produce the final composite score for each cognitive domain (see Supplementary Table 1B). As cognitive tasks were administered in a fixed order, composite scores drew on tasks from both earlier and later stages, reducing the likelihood of domain-specific bias due to order effects.

Statistical methods

All statistical analyses were performed in R (version 4.4.1) and RStudio (version 2024.09.1). The code used for the analysis is based on the code from Mellow et al.[37] and can be found on GitHub (https://github.com/pjmarent/PASOCAcrosssectional.git).

To account for the co-dependency of the 24-hour movement behaviours, time-use data were analysed using a compositional data approach[29]. Using the 'closure' function from the 'compositions' package[64], all time-use compositions were normalised to sum up to 24 hours. There were no zero values observed for any of the 24-hour movement behaviours. Next, following published procedures[65], a sequential binary partition matrix was constructed to compute three isometric log-ratios (ILRs). These were organised as follows: 1) sleep over wakefulness (SB, LPA and MVPA); 2) inactivity (SB) over activity (LPA and MVPA); 3) light activity (LPA) over moderate-to-vigorous activity (MVPA). These isometric log-ratio coordinates were subsequently entered as predictors into multiple regression models.

For each of the four cognitive composite scores, four general linear models were constructed. The first model only included the full set of ILR-transformed time-use coordinates as predictors. Subsequent models progressively expanded this first model by adding sociodemographic (model 2: + age, sex, education level and living situation), health (model 3: + BMI category, total number of prescribed medications and hearing status) and health-behaviour covariates (model 4: + alcohol use and smoking status). All assumptions underlying multiple regression were checked using the R 'performance' package[66] and for the models of short-term memory and executive functions all were met. However, for long-term memory and processing speed the assumption of normality of residuals was violated, thus a log-transformation was applied to the dependent variable. In addition, the model for long-term memory included an additional covariate, namely 'time interval' (see Supplementary Table 1A for more information on this variable). In short, this covariate is the time interval in seconds between the presentation phase and the recall phase.

Next, the R package 'model summaries' provided an overview of the fit of each model and the estimated coefficients of the predictors[67]. The Akaike Information Criterion (AIC) then identified the most parsimonious model among the four models. Following this selection, an ANOVA type II test assessed the significance of each individual predictor. The ILR coordinates are not interpreted individually; instead, they jointly represent the compositional nature of time use. Therefore, a single F-statistic is reported for time use, reflecting the combined effect of the three ILR coordinates.To account for multiple comparisons, p-values in the final model were corrected using the robust Benjamini-Hochberg procedure to control the false discovery rate (FDR)[68]. Both the original p-values and those adjusted for multiple testing are reported. The significance level was set at $\alpha = 0.05$ level both before and after the FDR adjustment. If time use remained significantly associated after adjusting for multiple comparisons, hypothetical time reallocations were conducted to explore the meaning and direction of this association. This analysis was performed using the R-package "codaredistlm", which calculates the hypothetical mean difference in the cognitive composite score by reallocating time in 5-minute intervals (ranging from −30 to +30 minutes). One-for-one reallocations were performed for all possible behaviour pairs (e.g. reallocating time from LPA to sleep, from SB to MVPA…) while keeping all other behaviours constant. Additionally, proportional reallocations were conducted for each of the four behaviours, by reallocating time to one behaviour (e.g. sleep) proportionally taken from the remaining three (e.g. SB, LPA and MVPA)[69]. Importantly, the hypothetical results of time reallocations on the cognitive outcomes are always relative to the average composition of this sample.

Results

Sample characteristics

Of the 260 older adults who initially provided informed consent, 27 participants were excluded based on their MoCA-scores (≤ 23; $n = 19$), other exclusion criteria ($n = 5$), withdrawal ($n = 1$) and device errors ($n = 2$). The final sample consisted of 233 participants (51.1% female), with a median age of 68.2 years (IQR 61.9–73.3, range 55–90 years) and 62.7% having higher education. While all 233 participants provided data for short-term memory and processing speed, missing components of the cognitive composite score in some cases led to a smaller dataset for long-term memory ($n = 232$) and executive functioning ($n = 231$). A detailed overview of the participants' characteristics is presented in Table 1.

The composition of time spent in total physical activity (LPA and MVPA together), sedentary behaviour and sleep is visualised in Fig. 1. This ternary diagram depicts both individual compositions in light blue and the overall compositional mean in dark blue, showing that participants on average allocated 15.1% of their day to PA (3.6 hours; approximately 10% LPA and 5% MVPA on average), 53.5% to SB (12.9 hours) and 31.4% to sleep (7.5 hours).

	Total ($n = 233$)	
Age (years) (median (IQR))	68.2	(61.9–73.3)
Sex		
Male	114	(48.9)
Female	119	(51.1)
Education		
Low	28	(12.0)
Middle	59	(25.3)
High	146	(62.7)
Living together with partner/family/friends		
No	49	(21.0)
Yes	184	(79.0)
BMI (kg/m^2)		
Healthy weight (18.5–24.9)	109	(46.8)
Overweight (25–29.9.9)	96	(41.2)
Obesity (≥ 30)	28	(12.0)
Total number prescribed medications (median (IQR))	1	(0–3)
Hearing issues (% none)		
None present	153	(65.7)
Present	80	(34.3)
Alcohol		
Daily	42	(18.0)
Weekly	119	(51.1)
Occasionally (monthly, less than monthly)	52	(22.3)
Never	20	(8.6)
Smoking		
Never	136	(58.4)
Former	92	(39.5)
Current	5	(2.1)
Time use (arithmetic median (IQR))		
Sedentary Behaviour (min/day)	759	(708–819)
Light PA (min/day)	155	(120–181)
Moderate-to-Vigorous PA (min/day)	70	(45–98)
Sleep Period Time (min/day)	451	(422–475)
Time use (compositional mean (% day))		
Sedentary Behaviour (min/day)	774	(53.7)
Light PA (min/day)	148	(10.3)
Moderate-to-Vigorous PA (min/day)	64	(4.5)
Sleep Period Time (min/day)	454	(31.5)

Table 1. Characteristics of participants. All values are n (%) unless stated otherwise. IQR, Interquartile Range; BMI, Body Mass Index; PA, Physical Activity; min, minutes. Compositional mean adds up to 1440 min (24 hours).

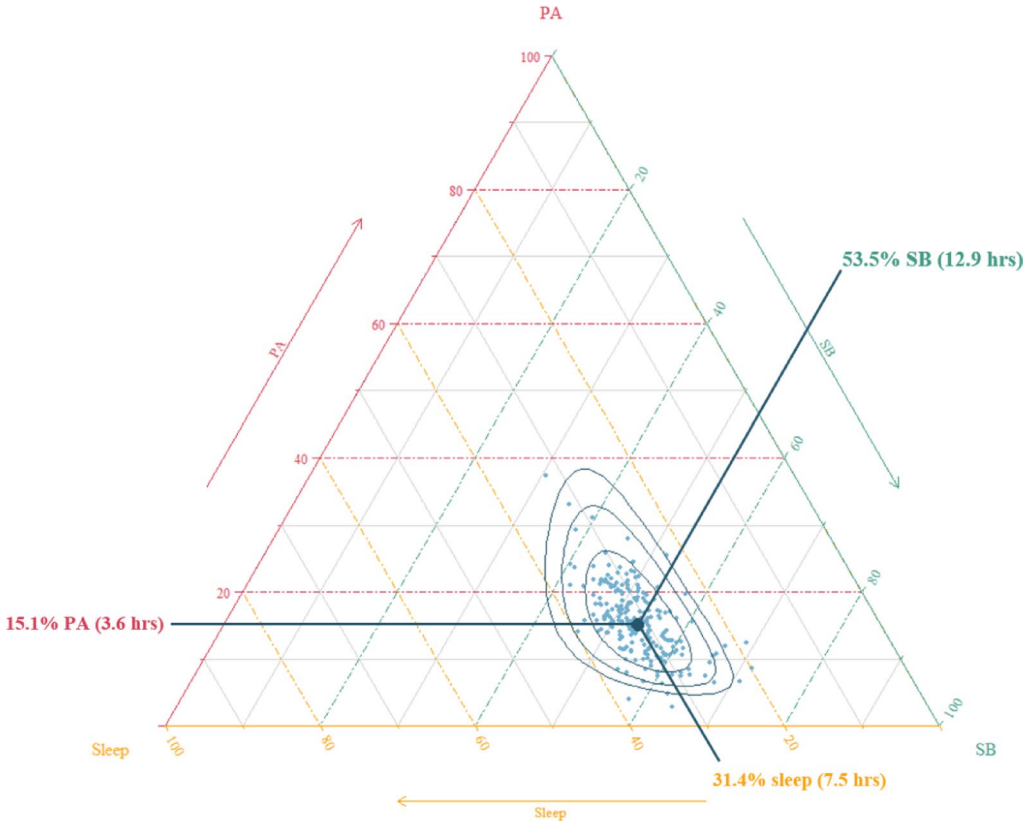

Fig. 1. Ternary diagram of time use. Ternary diagram with each vertex representing 100% time use in a specific behaviour (i.e. Physical Activity (PA); Sedentary Behaviour (SB); Sleep). The relative contribution of each time-use behaviour at any point within the triangle can be identified by drawing a line parallel to the base opposite the vertex of interest. For instance, the dark blue dot – representing the compositional mean with three ellipses representing the 75, 95 and 99% confidence intervals – indicates this sample spends on average 53.5% of their day in SB, 31.4% in sleep and 15.1% in PA (approximately 10% LPA and 5% MVPA on average). The compositional mean differs from the arithmetic median presented in Table 1 as it reflects the central tendency of the compositional data, accounting for the relative proportions across all three behaviours, whereas the median represents the midpoint of each behaviour independently. LPA and MVPA are combined as PA to simplify the figure, as four compositions would require an extra dimension, which is not feasible in a 2D plot. Nevertheless, the compositional mean for all four components can be found in Table 1. Hrs, hours.

Associations of time use with cognitive outcomes

For each of the four cognitive composite scores, Model 2, which included time use and sociodemographic factors as independent variables, was the most parsimonious model. It demonstrated a statistically significant overall fit for short-term memory ($F_{(8,224)} = 10.75$, $p < 0.001$, adjusted $R^2 = 0.25$), long-term memory ($F_{(9,222)} = 10.75$, $p < 0.001$, adjusted $R^2 = 0.09$), executive function ($F_{(8,222)} = 16.04$, $p < 0.001$, adjusted $R^2 = 0.34$) and processing speed ($F_{(8,224)} = 2.19$, $p = 0.03$, adjusted $R^2 = 0.04$). See Supplementary Table 2 for an overview of all the estimates.

The ANOVA type II test further revealed statistically significant associations of time use with short-term memory, long-term memory and executive function, but not with processing speed. Associations for short-term memory and executive function remained statistically significant after adjusting for multiple testing (see Table 2).

For *short-term memory*, hypothetically reallocating time to MVPA from any other behaviour was significantly associated with better short-term memory z-scores (see Fig. 2A). Specifically, reallocating just 5 minutes to MVPA from LPA, sleep or SB was associated with significant mean differences of 0.03 [95% Confidence Interval 0.01, 0.06], 0.03 [0.01, 0.04] and 0.02 [0.01, 0.04], respectively. The largest hypothetical differences were observed with a 30-minute reallocation to MVPA, resulting in mean differences of 0.19 [0.05, 0.32] when time was reallocated from LPA, 0.15 [0.06, 0.23] from sleep and 0.12 [0.05, 0.19] from SB. Alternatively, reallocating time away (even as little as 5 minutes) from MVPA to any other behaviour was significantly associated with lower short-term memory z-scores. For example, taking 30 minutes from MVPA was associated with significant mean differences of −0.26 [−0.42, −0.09] when reallocated to LPA, −0.23 [−0.36, −0.10] to sleep and −0.20 [−0.31, −0.08] to SB.

For *executive function*, hypothetically reallocating time to MVPA from any other behaviour was significantly associated with better executive function z-scores (see Fig. 2B). Specifically, reallocating just 5 minutes to MVPA from LPA, sleep or SB was associated with significant mean differences of 0.04 [0.02, 0.06], 0.02 [0.01, 0.04] and 0.02 [0.01, 0.03], respectively. The largest hypothetical differences were observed with 30 minutes reallocated to

	Short-term memory ($n = 233$)			Long-term memory ($n = 232$)			Executive function ($n = 231$)			Processing speed ($n = 233$)		
	$F_{(n, d)}$	*p*-value	adj.*p*	$F_{(n, d)}$	*p*-value	adj.*p*	$F_{(n, d)}$	*p*-value	adj.*p*	$F_{(n, d)}$	*p*-value	adj.*p*
Time use	$4.17_{(3,224)}$	**0.007**	**0.011***	$2.71_{(3,222)}$	**0.046**	0.092	$6.04_{(3,222)}$	**0.001**	**0.001***	$1.32_{(3,224)}$	0.269	0.365
Age	$8.94_{(1,224)}$	**0.003**	**0.008***	$2.02_{(1,222)}$	0.157	0.188	$32.57_{(1,222)}$	**< 0.001**	**< 0.001***	$1.19_{(1,224)}$	0.276	0.365
Sex	$5.36_{(1,224)}$	**0.022**	**0.027***	$2.15_{(1,222)}$	0.144	0.188	$1.94_{(1,222)}$	0.165	0.206	$1.00_{(1,224)}$	0.319	0.365
Education	$12.05_{(2,224)}$	**< 0.001**	**< 0.001***	$4.33_{(2,222)}$	**0.014**	**0.043***	$7.85_{(2,222)}$	**0.001**	**0.001***	$1.01_{(2,224)}$	0.365	0.365
Living arrangement	$0.24_{(1,224)}$	0.622	0.622	$0.05_{(1,222)}$	0.817	0.817	$0.02_{(1,222)}$	0.898	0.898	$1.74_{(1,224)}$	0.188	0.365
Time interval (sec)	-	-	-	$11.02_{(1,222)}$	**0.001**	**0.006***	-	-	-	-	-	-

Table 2. Statistical results of ANOVA type II F-tests for the parsimonious model of each cognitive outcome. F(*n*, d), F statistic, numerator and denominator degrees of freedom; *adj.p*, p-value adjusted for false discovery rate; sec, seconds. Bold denotes statistical significance ($p < 0.05$). * Denotes p-values that remained significant after false discovery rate adjustment. "-" denotes variable that was not included in model. Time interval is the duration between stimulus presentation and testing.

MVPA, resulting in mean differences of 0.21 [0.10, 0.33] when time was reallocated from LPA, 0.13 [0.06, 0.20] from sleep and 0.08 [0.02, 0.14] from SB. Additionally, reallocating time from LPA to either sleep or SB, as well as shifting time from sleep to SB, was significantly associated with better executive function z-scores. For instance, shifting 30 minutes from LPA to sleep or SB predicted mean differences of 0.08 [0.01, 0.16] and 0.13 [0.06, 0.20], respectively, while reallocating 30 minutes from sleep to SB was significantly associated with a difference of 0.05 [0.01, 0.09]. Alternatively, reallocating time away (even as little as 5 minutes) from MVPA to any other behaviour was significantly associated with poorer executive function z-scores. For example, taking 30 minutes from MVPA was linked to significant mean differences of −0.26 [−0.40, −0.12] when reallocated to LPA, −0.19 [−0.31, −0.08] to sleep and −0.15 [−0.25, −0.05] to SB. Additionally, reallocating 30 minutes away from SB to LPA or sleep was associated with significant mean differences of −0.11 [−0.17, −0.06] and −0.05 [−0.09, −0.01], respectively.

Supplementary Tables 3–6 provide a full overview of all hypothetical reallocations, as well as the mean differences of reallocating time to one behaviour from all other behaviours proportionally. In short, a positive hypothetical mean difference in z-score is found for both short-term memory and executive function, when reallocating time to MVPA proportionally.

Discussion

With a globally ageing population, addressing age-related cognitive decline is becoming increasingly important for maintaining quality of life at an older age. While lifestyle behaviours such as physical activity, sedentary behaviour and sleep are known to play a crucial role in healthy ageing, research has often studied them in isolation, overlooking the interdependent nature of these time-use behaviours. To bridge this gap, this study used a holistic approach by exploring the associations between 24-hour movement behaviours (i.e. light physical activity, moderate-to-vigorous physical activity, sedentary behaviour and sleep) and several cognitive function domains, including short-term memory, long-term memory, executive functioning and processing speed in community-dwelling adults aged 55 and older. The findings highlight the critical role of time use for cognitive health, with specific associations observed for both short-term memory and executive functioning. Additionally, the exploration of hypothetical reallocations of time between the different behaviours provided a unique insight into more targeted time-use intervention strategies for improved cognition. In particular, reallocating time to MVPA from any other behaviour shows potential as a beneficial approach.

The importance of time reallocation to MVPA for optimising different domains of cognitive function is consistent with previous research. A systematic review by Mellow et al.[70] examining the relationship between PA, SB and sleep with cognition in older adults reported that higher proportions of MVPA were most often associated with better general cognition. The review included 23 studies, all involving healthy older adults (average age of 71.3 ± 5.4 years), with five studies also including subgroups of older adults with cognitive decline, MCI, dementia or MS. However, most of the included studies focused on just two time-use behaviours, with only four studies measuring all three. One example of a study with three time-use measures is Fanning et al.[71], which used device-based measures for PA and SB, alongside self-reported sleep in healthy older adults (mean age 65.4 ± 4.6 years). They found positive associations for executive function when 30 minutes of SB was replaced by 30 minutes of MVPA. Next, Wei et al.[72], analysed NHANES self-reported data and found that in older adults aged 60 and above who slept seven hours or less, reallocating 30 minutes of SB to MVPA was positively related to general cognition, as well as executive function, processing speed and language. When sleeping more than seven hours, reallocating 30 minutes from sleep to any other time-use behaviour was beneficially associated for several cognitive domains. Additionally, reallocating the same amount of time from LPA towards MVPA or SB was associated with improved executive function and processing speed. While both studies included all time-use behaviours within a single model, they addressed the compositional nature of the data differently by analysing time use in absolute units within an isotemporal substitution model. Dumuid et al.[35], on the other hand, did apply compositional isotemporal substitution in their study examining the potential moderating effect of a genetic dementia risk factor (i.e. APOE ε4) on the relationship between time use and cognition in middle aged-to-older adults (aged 65.6 ± 7.5 years). They also concluded that proportionally reallocating time from the other

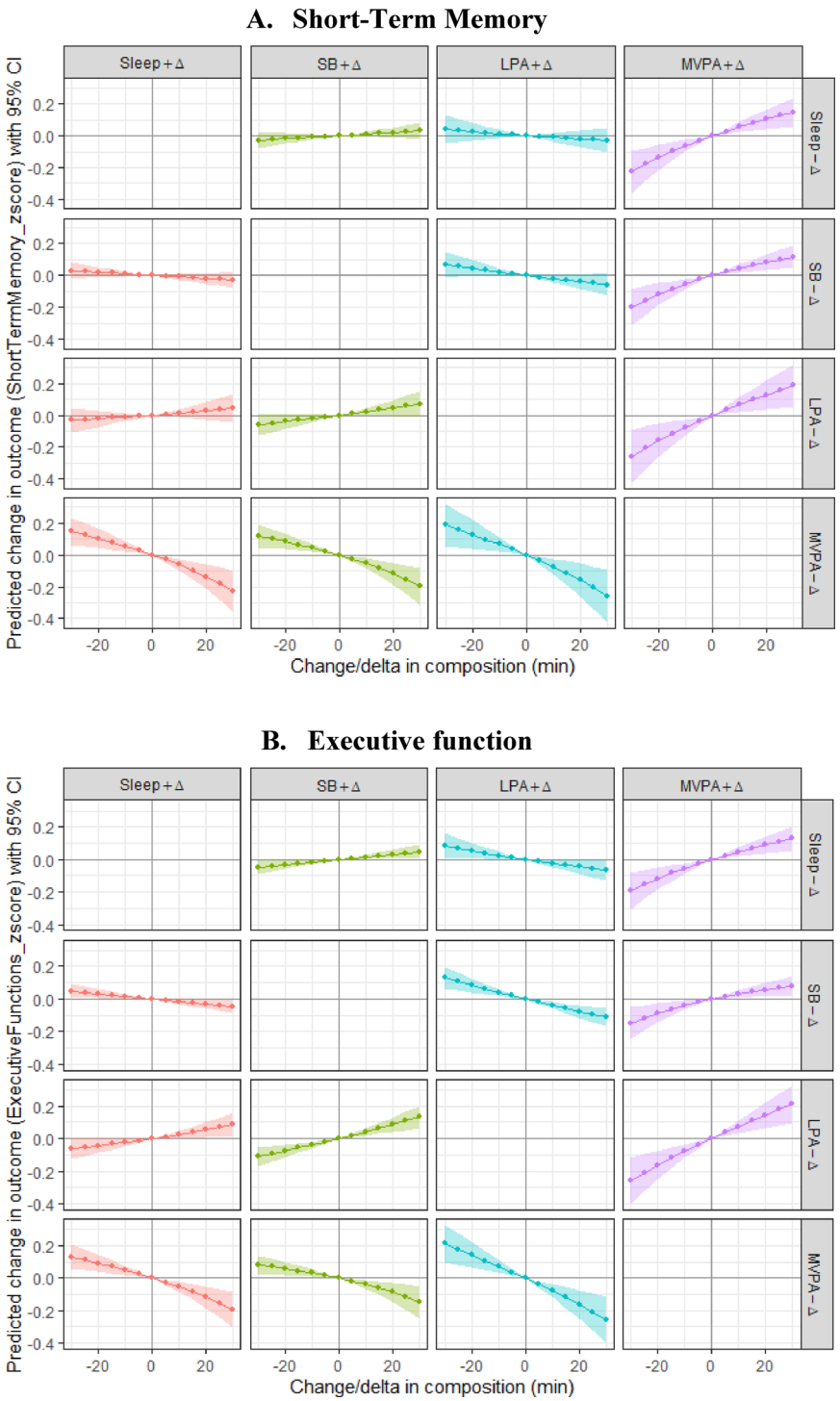

Fig. 2. Hypothetical time reallocations and their associated mean differences in cognitive z-scores. Panel A displays the predicted mean difference in short-term memory z-scores on the y-axis, with the x-axis representing time reallocations (− 30 to + 30 min/day). Panel B shows the predicted mean difference in executive function z-scores on the y-axis, with the x-axis representing the time reallocations. Time is reallocated in 5-minute increments between one pair of behaviours while all others remain constant. Behaviour-Δ indicates time removed from that behaviour and reallocated to the behaviour+Δ, with Δ representing the amount of reallocated time. SB, sedentary behaviour; LPA, light physical activity; MVPA, moderate-to-vigorous physical activity. Both models were adjusted for age, sex, education level, and living situation (Model 2).

behaviours to MVPA was positively associated with cognitive outcomes, with the association being even more pronounced in APOE ε4-carriers. Finally, Feter et al.[34] used device-based measures for PA and SB alongside diary-assessed sleep within the compositional framework in community dwelling adults aged 58.9 (±8.6) years and reported better cognitive function scores when replacing 30 minutes of SB with MVPA. The results of this study extend these earlier observations by applying the compositional framework with device-based measures for all three time-use behaviours, while also testing multiple cognitive domains. Overall, the consistent findings across studies reinforces the potential of redirecting time use towards MVPA for cognitive health in middle-aged and older adults.

Statistically significant associations do not automatically imply that results have meaningful impact. To assess relevance, it is important to also consider the magnitude of the differences. The observed mean differences in z-scores in PASOCA are comparable in size to those found by Feter et al.[34]. For example, the present study found significant mean differences of 0.19 (95% CI: 0.05, 0.32) for short-term memory z-scores and 0.21 (95% CI: 0.10, 0.33) for executive function with a 30-minute reallocation from LPA to MVPA. Similarly, in Feter et al.[34], reallocating 30 min from SB to MVPA was associated with mean differences of 0.14 (95% CI: 0.12–0.17) in z-score for global cognition. Importantly, differences of this magnitude may have meaningful implications for slowing cognitive decline over time, as suggested by Feter et al.[34]. To support this theory, they referenced Zhu et al.[73], who reported a yearly decline in executive function of −0.01 z-score in older adults ($N = 6452$, 69.7 ± 8.5 year) over a 3-year follow-up period.

Furthermore, beyond the consistency of these associations including similar magnitudes, the biological pathways underlying the cognitive benefits of sufficient PA have already been identified and conceptualized at several levels. These include (1) the cellular and molecular level, involving PA modulating key grow factors (e.g. BDNF) and promoting angiogenesis and neurogenesis and (2) the brain health level, involving structural changes in grey and white matter and higher activation of prefrontal cortex when being sufficiently physically active[74]. Given the biological plausibility – an essential component of Hill's causality criteria – these PA-cognition associations could be indicative of a causal relationship, although the cross-sectional nature of the data limits the ability to rule out reverse causality[75]. However, future research, particularly randomized controlled trials, is essential to more robustly support causality and clarify the directionality of these associations.

Interestingly, Mellow et al.[37] did not observe any significant association between time use and cognition in healthy older adults (age 65.5 ± 3.0 years), despite employing a rigorous method with device-based measures and compositional data analysis, similar to this study. They used wrist-worn actigraphy to capture all three time-use behaviours, assessed cognition with CANTAB tests and applied a statistical approach to analyse the data which formed the basis for this study's code. However, the cognitive composite scores were constructed slightly differently in both studies. In PASOCA, the composite score for short-term memory and executive function both included one additional test, potentially offering a more comprehensive assessment of these cognitive domains (see Supplementary Table 1). Nevertheless, when repeating the PASOCA analyses for short-term memory and executive function using the same composite scores as Mellow et al.[37], associations remained statistically significant for executive function ($p < 0.05$) and border-line significant for short-term memory ($p = 0.06$) after FDR-adjustment. This suggests that the differences in findings are not solely attributable to the inclusion of additional tests but may also reflect other methodological or sample-related factors. For instance, Mellow et al.[37] examined a slightly higher active sample ($n = 384$), with participants spending on average 18.5% of their day in PA (89 ± 47 min of MVPA, mean ± SD), compared to 15.1% in the current study (74.8 ± 41 min of MVPA, mean ± SD). Additionally, their sample was highly educated with a mean of 16.5 (± 3.2) years, resulting in high cognitive scores with small variability. PASOCA also included a relatively high proportion of highly educated participants (see Table 1) but still nearly 40% of the sample had maximum 12 years of education. Finally, methodological differences in accelerometer data processing could also contribute to the different findings. For example, Mellow et al.[37] did not mention any calibration of the acceleration sensor, which could be a potential source of error and leading to higher PA values[55]. Overall, while they did not observe any significant association of time use with cognition, the overall consistency of findings across multiple studies, including PASOCA, suggests that time use warrants further exploration under different conditions and varying populations.

The association of PA with cognition found in this study seems to be intensity-dependent as the hypothetical reallocation of time from sleep or SB to LPA predicted no positive differences at all, while time reallocations towards MVPA did. Moreover, it even was associated with poorer z-scores for short-term memory when time from MVPA would go to LPA, as well as for executive function when time was reallocated from MVPA, SB or sleep to LPA (see Supplementary Tables 3–6). In contrast, reallocating time from LPA or sleep to sedentary behaviour demonstrated better executive function z-scores. These findings challenge the conventional general health narrative emphasizing the positive role of LPA, as other health outcomes such as mortality, waist circumference and metabolic syndrome often show significant benefits from increased LPA[76]. However, reallocating time from LPA or even sleep to SB could be advantageous, potentially due to cognitively engaging sedentary activities such as reading, socializing or computer work[24,77]. Nonetheless, it remains crucial to emphasize that replacing SB with MVPA, seems to be associated with better cognitive outcomes overall. This underscores the complex and context-dependent nature of SB in cognitive outcomes, where the type of sedentary activity plays a pivotal role in shaping its association with cognition.

This study has several strengths. First, the use of robust measurement tools for assessing the 24-hour movement behaviours and several cognitive domains, as well as adapting a compositional framework, allows for a deeper understanding on how these behaviours collectively affect cognitive ageing. Next, the creation of cognitive composite scores allowed for a more comprehensive assessment of the different cognitive domains. In addition, this study carefully considered and included a range of factors associated with cognitive function as covariates. However, there are several limitations. First, wrist-worn accelerometery processed through GGIR captures 'inactivity' which may not fully reflect sedentary behaviour as it does not differentiate between standing

and sitting or lying down. Additionally, the small number of naps recorded in the participants' diaries were classified as 'inactivity' rather than daytime sleep episodes, as GGIR currently does not support nap detection for older adults. Second, the cross-sectional design limits the ability to draw causal conclusions about the observed associations. Third, contextual information about the cognitive demands of specific activities, particularly within the sedentary behaviour category, was lacking. Similarly, both light and moderate-to-vigorous PA encompass a wide range of behaviours (e.g. incidental movement, household chores, structured exercise or socially engaging tasks) that may differ in their cognitive relevance[77]. Future studies could consider more detailed categorization or contextual assessment of these behaviours to better capture these nuances. Finally, this study's sample is not fully representative of the general population, as it included a higher proportion of highly educated individuals compared to the general Belgian population of middle-aged to older adults. Moreover, the exclusion criteria specifically targeted health conditions potentially associated with cognition and 24-hour movement behaviours, which may have introduced healthy volunteer bias and limits the generalizability of our findings to broader populations with more diverse health profiles.

Overall, this study extends the current evidence from the, to the best of our knowledge, only two other studies that similarly captured all time-use behaviours without completely relying on subjective input from participants for one of them (often sleep)[35,37]. Collectively, results from these studies – including the present one – suggest that physical activity, sedentary behaviour and sleep may be better understood when examined together as interrelated components of daily time use. This integrated approach provides a more holistic view of how time-use dynamics relate to cognitive health. Based on current evidence, health promotion and behaviour change strategies should focus on increasing time spent in MVPA when considering cognitive health outcomes. However, more studies are needed to replicate and extend these findings. Future research should adopt a longitudinal design to better understand the temporality between movement behaviours and cognitive function in older adults. Additionally, incorporating more detailed assessments could enrich the data on the cognitive demands of various activities, including sedentary, but also physical ones. Exploring the interaction between movement behaviour patterns and cognitive load will help refine strategies for optimizing daily activity to promote cognitive health at older age.

Data availability

The script used to process the accelerometery data and to analyse the data is provided within the manuscript (see GitHub link in methods section). The data are available from the authors upon reasonable request.

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Author contributions

P-J M, GA, GC, and JvU contributed to the conceptualization and design of the study. Data acquisition was carried out by P-J M, data analysis and interpretation of the data was conducted by P-J M and DD. The manuscript draft was prepared by P-J M, with GA, DD, GC, and JvU providing critical revisions. All authors reviewed and approved the final version of the manuscript.

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Declarations

Competing interests

The authors declare no competing interests.

Additional information

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