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Optimal levels of sleep, sedentary behaviour, and physical activity needed to support cognitive function in children of the early years

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Abstract

Background Sleep, sedentary behaviour, physical activity, and the composition of these movement behaviours across the 24-h day are associated with cognitive function in early years children. This study used a Goldilocks day compositional data analysis approach to identify the optimal duration of sleep, sedentary behaviour, light physical activity, and moderate-to-vigorous physical activity associated with desired cognitive function outcomes in early years children.

Methods This cross-sectional study included 858 children aged 2.8–5.5 years from the Sleep and Activity Database for the Early Years. 24-h movement behaviours (sleep, sedentary behaviour, light physical activity, moderate-to-vigorous physical activity) were measured using ActiGraph accelerometers. Cognitive function was measured using three tasks from the Early Years Toolbox: visual-spatial working memory, response inhibition, and expressive vocabulary. A Goldilocks day compositional data analysis approach was used in R software to identify the optimal time-use compositions associated with the best 10% of the cognitive function scores.

Results The movement behaviour composition and the relative time spent in sleep and sedentary behaviour but not different intensities of physical activity were significantly associated with working memory ($P \leq 0.01$). The movement behaviour composition and relative time spent in sleep, sedentary behaviour, and different intensities of physical activity were not significantly associated with response inhibition or expressive vocabulary ($P > 0.2$). Therefore, optimal time use was only determined for working memory. Optimal daily durations for working memory were observed with 11:00 (hr:min) of sleep, 5:42 of sedentary behaviour, 5:06 of light physical activity, and 2:12 of moderate-to-vigorous physical activity.

Conclusion Working memory was the only cognitive function outcome related to the 24-h movement behaviour composition. Optimal sleep for working memory was consistent with current recommended durations, while optimal moderate-to-vigorous physical activity greatly exceeded minimal recommended levels. Optimal sedentary behaviour was longer and light physical activity was shorter than the sample average.

Keywords Cognition, Time use epidemiology, Compositional data analysis, Movement behaviours, Early childhood, Preschool

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Introduction

The early years, defined here as the first 6 years of life, are a critical period for the development of cognitive function [1, 2]. An important component of cognitive function is executive function, which refers to a collection of cognitive processes crucial for self-control and achieving goals in the early years [3]. These cognitive processes include working memory (ability to hold and manipulate information over short periods), response inhibition (capacity to suppress impulsive behaviours and resist distractions), and cognitive flexibility (adaptation of thinking in response to fluctuating environments) [1–3]. Additionally, executive functions involve emotional regulation and vocabulary development [1, 2]. Early cognitive function predicts a range of later-life outcomes including school readiness, academic achievement, behavioural issues, and quality of life [2, 4, 5]. Therefore, it is important to optimize cognitive function in the early years.

Systematic reviews have concluded that adequate sleep, high levels of physical activity (PA), and low levels of some sedentary behaviours (SED), particularly screen time, are associated with better cognitive function in the early years [6–8].The proposed neurobiological pathways by which movement behaviours influence cognitive function in the early years differ for sleep, PA, and SED. Sleep positively influences physiological mechanisms that improve neuroplasticity and aid in consolidating memory skills [9]. A cohort study found that early years children who sleep within the recommended range of 11 to 14 h have better cognitive function than children who sleep less or more [10]. PA is positively associated with brain angiogenesis, synaptogenesis, neurogenesis, and the regulation of neurotrophic factors [11]. For example, a clustered randomized-control study found significant improvements in word recall after physical activity interventions [12]. Excessive SED, namely sitting time, may impact neurogenesis (a critical process for learning and memory) via increased activation of stress systems and impaired synaptic plasticity [13]. Screen time is proposed to have a negative association with cognitive processes by impacting brain white matter [14]. A longitudinal cohort study of 2,441 children examined at ages 2, 3, and 5 years found that children who spent more time using screens at ages 2 and 3 years showed significantly lower scores on developmental tests when they were 3 and 5-years-old, respectively. Specifically, increased screen time at 2 years of age was associated with decreased performance on developmental assessments at 3 years of age ($\beta = -0.06$, 95% CI: -0.10 to -0.01) [15].

Recent research suggests that the composition of movement behaviours across the 24-h day influences cognitive function in early years children [16, 17]. Furthermore, substituting time across movement behaviours may influence cognitive function. For example, a study of 135 preschoolers found that substituting sleep or SED with an equivalent duration of MVPA was associated with a positive changes in cognitive flexibility [16]. Another study of 426 preschoolers observed that increasing time in MVPA at the expense of decreasing time in SED or sleep was associated with improved inhibitory control [18]. Public health guidelines for movement behaviours from the World Health Organization [19] and several individual countries (e.g., Canada [20], Australia [21], New Zealand [22], and South Africa [23]) recommend that 3-to 4-year-olds get 10–13 h/day of sleep, limit their daily screen time to 60 min or less, and accumulate at least 180 min/day of PA including at least 60 min/day of moderate-to-vigorous PA (MVPA). Although these recommendations take an integrated approach and address movement across the full day, they are primarily based on evidence from studies that examined individual movement behaviours [24, 25]. Because movement behaviours are co-dependent variables constrained to 24 h a day, they should be examined simultaneously when studying their health benefits [24, 25]. Furthermore, the guideline recommendations do not provide information on the optimal duration for these behaviours. Rather, they suggest a healthy range for sleep, a minimum amount of PA, and a maximum allowable screen time. The optimal amount of time that a preschooler should spend in each movement behaviour is unknown and should be investigated using analysis approaches that take their combined influence into account.

Compositional data analysis (CoDA) can be used to determine the optimal time-use composition of all movement behaviours [24–26]. Dumuid and colleagues have coined the optimal CoDA zone as the "Goldilocks day"; the movement behaviour composition that is just right for different health outcomes [26, 27]. A study of 11-to 12-year-olds suggested that the Goldilocks day that equally weights physical, mental and cognitive health outcomes is comprised of 10:21 (hr:min) of sleep, 9:44 of SED, 2:26 of light PA (LPA), and 1:29 of MVPA [27].

To the best of our knowledge, the Goldilocks day or optimal time use CoDA approach has not been used in early years children. Therefore, the objective of this study was to use this approach to identify the optimal duration of sleep, SED, LPA, and MVPA related to desired cognitive function indicators in the early years.

Methods

Study design and participants

The data used in this study were obtained from the Sleep and Activity Database for the Early Years (SADEY),

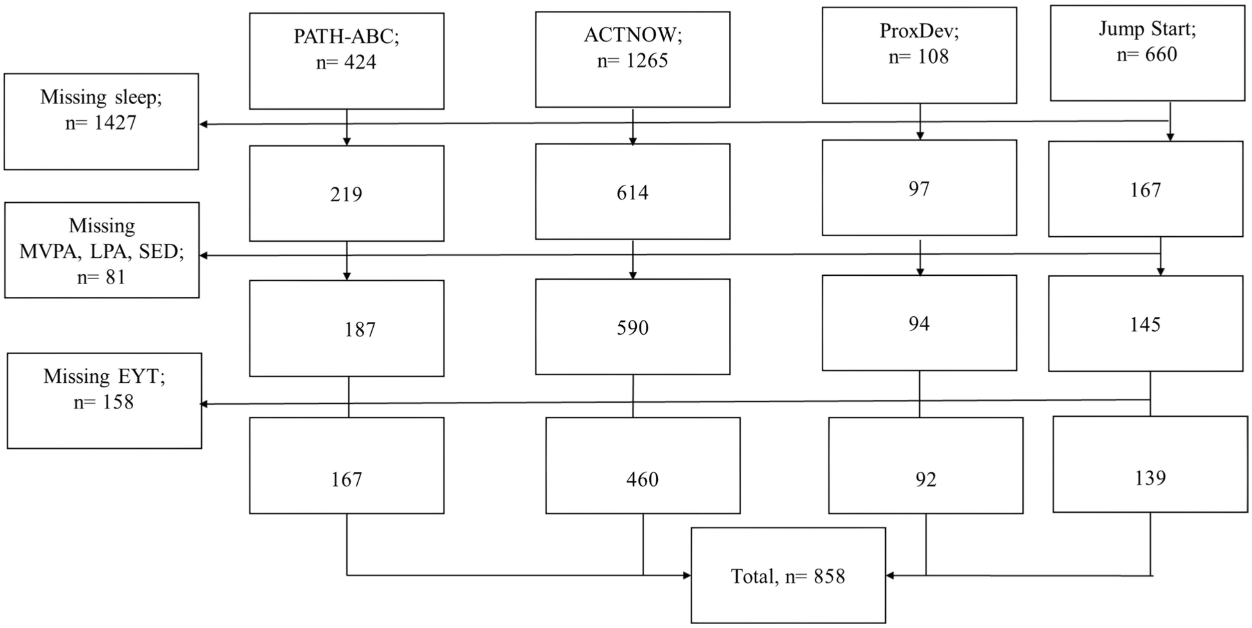

Fig. 1 Flow chart illustrating exclusion of participants with missing data. PATH-ABC: the Preschool Activity Technology, Health, Adiposity, Behaviour and Cognition study; Jump start: the childcare-based intervention to promote physical activity in pre-schoolers study; ACTNOW: the Active Learning Norwegian Preschool(er)s study; ProxDev: the Movement behaviours and physical, cognitive, and social-emotional development in preschool study; SED: sedentary behaviour; LPA: light physical activity; MVPA: moderate-to-vigorous physical activity; EYT: Early Years Toolbox

which is a consortium of pooled accelerometer-measured movement behaviour data in children aged 7 years or younger [28]. Informed consent to participate was obtained from a parent or legal guardian in each of the contributing studies. The initial wave of SADEY data contains waist-worn Actigraph accelerometer data collected on ~ 8000 children from 14 studies conducted in 7 countries between 2009 and 2019 [28]. Ethics approval was obtained for all contributing studies and SADEY [28]. Raw or epoch-level accelerometer data were obtained for all contributing studies and re-processed in a harmonized manner, further details of which are provided below and in a previous publication [28]. Additionally, measures of several health and developmental outcomes were pooled, although the availability of these measures varied across the studies that are part of SADEY [28].

For the current paper, cross-sectional data from four SADEY studies were included: the Preschool Activity Technology, Health, Adiposity, Behaviour and Cognition (PATH-ABC) study conducted in Wollongong, Australia [29]; baseline data from the childcare-based intervention to promote physical activity in pre-schoolers (Jump start) study conducted in Wollongong, Australia [30]; the Active Learning Norwegian Preschool(er)s (ACTNOW) study conducted in Sogndal, Norway [31]; and the Movement behaviours and physical, cognitive, and social-emotional development in preschool (ProxDev) study conducted in Edmonton, Canada [17]. Data from other SADEY studies were excluded as they did not include the cognitive outcomes examined in the current paper. After the removal of participants with insufficient accelerometer data and missing data for other study variables, a total of 858 children aged 2.8 to 5.5 years were included (Fig. 1). Chi-square tests determined that key sociodemographic characteristics (age, sex, parental marital status, parental education) did not differ between those included and excluded from the analyses ($P > 0.05$, see supplementary materials Table S1). A post-hoc power analysis conducted in G*power using an alpha of 0.05 and an effect size of 0.15 indicated that our study of 858 children achieved a 100% power.

Movement behaviours

Movement behaviours were measured using ActiGraph GT3X + or wGT3X-BT accelerometers (ActiGraph Corporation, Pensacola FL) that were worn on the right hip using a 24-h wear protocol. Accelerometer data were processed using R software R 4.2.2 [32]. Data reduction entailed reprocessing the original raw activity files from ActiGraph (.gt3x) or, if raw files were not available, count-based files with 15-s epochs (.agd) from each study. This process involved applying standardized, evidence-based guidelines [28]. Accelerometer data from all SADEY studies were collapsed into 60-s epochs for the processing of sleep data and 15-s epochs for the processing of SED and

PA data during waking hours [28]. This approach allows for more detailed capture of PA patterns while maintaining compatibility with sleep analysis methods. Accelerometer data processing started with the PhyActBedRest package, which identified the start and end points of each nighttime sleep period and each nap [33]. This package uses a decision-tree approach to determine bedrest, was developed and validated amongst preschoolers, and has good sensitivity (0.94), specificity (0.97), and accuracy (0.95) when compared to visual identification of sleep periods [33]. Non-wear time during sleep was defined as at least 90 min of consecutive zero counts with up to 2 min of non-zero interruptions [34]. There is no consensus in the literature about the minimum wear time for accurate sleep estimation. The validation study for the PhyActBedRest package used ≥ 3 or more nights with ≥ 6 h of wear time [33], which is the criteria we used for inclusion in the present analysis. The average daily time spent in nighttime sleep and naps were summed (midnight-to-midnight) and averaged across valid days to determine total sleep duration.

After sleep periods were identified, the remaining accelerometer data were processed using the PhysicalActivity package to determine the average daily time spent in SED, LPA, and MVPA [35]. In general, when estimating the consistency of accelerometer estimates of PA, SED, and sleep across days from a single measurement period (i.e., the internal consistency), the ActiGraph shows acceptable validity and reliability in young children [36, 37]. However, when comparing separate measurement periods (i.e., test–retest reliability) over the course of 2 weeks separated by up to a year, the ActiGraph shows moderate reliability [38]. Non-wear time during waking hours was identified as ≥ 20 min of consecutive zero counts [39]. At least 6 h of wear time during waking hours was required for a day to be considered valid and participants were required to have ≥ 3 valid days to be included in the analysis. The cut-points we used to distinguish SED from LPA (≤ 25 counts per 15-s, see Evenson et al. [40]) and LPA from MVPA (≥ 420 per 15 s, see Pate et al. [41]) are more accurate at classifying movement intensity among young children than other cut-points used in the literature [42].

Average sleep duration (including nighttime sleep and naps) was expressed as a proportion of 24 h. The remaining proportion of 24 h was used to normalize time spent in SED, LPA, and MVPA so that the total time in all movement behaviours for each participant summed to exactly 24 h. Sleep duration was not normalized for non-wear time because we assumed that children either wore or did not wear the accelerometer while sleeping and that non-wear time on valid 24-h periods would have occurred during waking hours. The average ± SD imputed time for waking non-wear time was 2:41 ± 1:22 (hr:min).

Cognitive function

Cognitive function was measured using the standardized Early Years Toolbox (EYT) protocol in all studies. The EYT is a battery of 5 tasks completed by children on a tablet computer while being supervised by a researcher [43]. Each task takes approximately 5–8 min to complete. In this study, three EYT tasks were used: 1) visual-spatial working memory (Mr. Ant), 2) response inhibition (Go/No-Go), and 3) expressive vocabulary [43]. Note that the vocabulary sub-outcome of the EYT was limited to 711 participants as only 3 of 4 studies (PATH-ABC, ACTNOW, and ProxDev) included it. The EYT response inhibition and expressive vocabulary scores have good to excellent internal consistency (Cronbach's alpha range: 0.84–0.95) [43]. The visual-spatial working memory, response inhibition, and expressive vocabulary scores have moderate to strong criterion validity (r range: 0.40–0.60) when compared with other validated measures from the National Institutes of Health's Toolbox and British Ability Scales [43].

For the Mr. Ant working memory task, children were asked to remember the locations of stickers placed on a cartoon ant and subsequently identify these locations after a short retention interval. The task progressed in difficulty across levels with three trials for each level to a maximum of eight levels. The task ended if a failure occurred on all three trials within a level, or if all eight levels were completed successfully. Scores were calculated as 1 point for each level in which at least 2 of 3 trials were completed correctly, plus an additional 1/3 of a point for every correct trial thereafter [43]. Scores for this task can range from 0 to 4; higher scores represent better working memory.

For the Go/No-Go inhibition task, children were asked to tap the tablet screen if they saw a fish, which occurred 80% of the time (Go), but avoid taping the screen when they see a shark, which occurred 20% of the time (No-Go). There are 25 fish or shark stimuli in each block/trial, adding to 75 stimuli if the whole test is completed. Scores were calculated as the proportion of correct Go stimuli multiplied by the proportion of omitted No-Go stimuli, with values closer to 1 reflecting better response inhibition [43].

For the expressive vocabulary task, children were asked to correctly label up to 45 pictures. If the child labeled a picture incorrectly, a researcher asked what else it could be named. This process continued until the child correctly identified the picture or until the researcher determined that the child could not provide the correct word. The test ended after six consecutive inaccurate descriptions. Scores were calculated by adding the total number of correctly labeled pictures [43]. Scores for this task can range from 0 to 45; higher scores represent better language ability.

Covariates

Age in months, sex (male or female), study (PATH-ABC, ACTNOW, Jump-Start, or ProxDev), highest parental education (< high school, high school, or > high school), and marital status (single parent or dual parent household) were controlled for as confounding variables in regression analyses. The selection of confounding variables was informed by the existing literature [44–48], limited to those collected across all contributing studies, and variables that could be meaningfully harmonized. The harmonization process for the marital status and education variables is provided in Table S2.

Statistical analysis

Statistical analyses were performed in R 4.2.2 [32] using the Compositions [49], zComposition [50], robCompositions [51], and robustbase [52] packages. Conventional descriptive statistics were determined for the variables of interest. Geometric means for time spent in each movement behaviour were adjusted to sum to exactly 24 h and calculated. No participants had zero values for any of the movement behaviour variables.

The Goldilocks day or optimal time use CoDA approach involved seven data analysis steps [27].

Step 1: Multiple linear regression models were used to examine the relationships between the movement behaviour composition and the three cognitive function outcomes (working memory, response inhibition, and vocabulary). Separate regression model was created for each of the three cognitive function outcomes. The independent variables in the models were sleep, SED, LPA, and MVPA (after they were transformed using an isometric log-ratio coordinate system) and the confounding variables (age, sex, study, parental education, and parental marital status) [53]. Regarding the isometric log-ratio coordinate system, since the composition consists of four parts (sleep, SED, LPA, and MVPA), three ilr transformed variables [$zi1$, $zi2$, $zi3$] for each movement behaviour were created based on sequential partition. As an example, the isometric log ratio coordinate system for MVPA was:

$zi1 = \sqrt{\frac{3}{4}} In \frac{MVPA}{\sqrt[3]{LPA \times SED \times sleep}}$, $zi2 = \sqrt{\frac{2}{3}} In \frac{LPA}{\sqrt[2]{SED \times sleep}}$, and $zi3 = \sqrt{\frac{1}{2}} In \frac{SED}{\sqrt[1]{sleep}}$

The regression coefficient and standard error related to the first ilr coordinate variable were used to examine if that specific movement behaviour (MVPA in this example) was significantly associated with the given outcome relative to time spent in the remaining movement behaviours. The R^2 was used to determine the goodness-of-fit of the models. The residuals of these linear regression models were normally distributed. Polynomial terms for the set of isometric log ratios were considered for all models and compared with the non-squared models. Because quadratic relationships were not indicated ($P > 0.1$), the non-squared models were used. Age and sex interaction terms were also explored. Because the p-values for these interaction terms were not significant, they were removed. Therefore, the independent variables in the final regression models were limited to the three variables in the isometric log-ratio coordinate system and the five confounding variables.

Step 2: A grid of predictive time-use compositions were generated. These predictive-time-use compositions represented every possible combination (in 10 min/day increments) of movement behaviours within the typical daily ranges observed in the study sample. This process started by creating a 4-demensional grid where the movement behaviour values were in 10-min increments and where the ranges for each of the movement behaviours extended beyond the ranges observed in our study sample (440–1000 min/day for sleep, 90–400 min/day for SED, 50–450 min/day for LPA, 0–175 min/day for MVPA). Next, we deleted all values from the grid where the combination of movement behaviours did not add up to exactly 24-h (1440 min). We then removed values from the grid if the sleep (521–883 min/day), SED (194–360 min/day), LPA (196–399 min/day), and MVPA (23–169 min/day) all did not fall within ± 3 SDs from the sample mean. This truncation was performed to trim the grid to values observed in the sample. This ensured that we would avoid making predictions (see *Step 3*) that were beyond the observed values in the sample. After removing values in the grid where all four movement behaviours did not fall with ± 3 SDs from the sample mean, the ranges of the movement behaviours were 540–880 min/day for sleep, 200–350 min/day for SED, 200–390 min/day for LPA, and 30–160 min/day for MVPA. The result was a 3D grid of 4,025 predictive time-use composition data points representing hypothetical children within the movement behaviour composition footprint of our dataset.

Step 3: The linear regression models developed in *Step 1* were used to estimate each of the cognitive function outcomes for each of the 4,025 predictive time-use compositions developed in *Step 2*. None of the predicted values exceeded the range of data observed in our study sample.

Step 4: The "best" time-use zone was defined for each cognitive function outcome as the predictive time-use compositions associated with the best 10% of the cognitive function scores of the sample. Dumuid et al. [26] defined the best time-use zone based on the best 5%; however, because our sample was much smaller than theirs (858 vs. 1874 participants), we used the best 10% to increase the overlapping area between the "best" time-use zones of the individual cognitive function outcomes.

Step 5: The "optimal" time-use composition for each cognitive function outcome was defined as the centre (compositional mean) of the "best" time-use zone.

Step 6: The "best of the best" time-use zone was identified as the overlapping areas of the "best" time-use zones for the individual cognitive function outcomes. Only the cognitive function outcomes that were statistically significantly associated with movement behaviour composition in *Step 1* were included in this step of the analysis.

Step 7: The centre of the overlapping "best of the best" time-use zones was identified and hereafter referred to as the "optimal" (Goldilocks day) composition.

Sensitivity analyses were performed to determine if the accelerometer processing decision influenced the findings. This included rerunning the analyses after changing the valid day criteria from ≥ 6 h to ≥ 8 h, the number of valid days from ≥ 3 to ≥ 4, and using the Trost et al. [54] cut-points to distinguish SED, LPA, and MVPA.

Table 1 Participant characteristics

Variable	n (%) or mean (SD)
Age, mean (SD)	4.2 (0.7)
Sex, n (%)	
Boys	474 (55.1)
Girls	387 (44.9)
Parental education, n (%)	
< high school	53 (6.2)
high school	125 (14.5)
> high school	622 (72.2)
Marital status, n (%)	
Dual parent	720 (83.6)
Single parent	78 (9.1)
Cognitive outcome measures, mean (SD)	
Working memory (range: 0–4)	1.37 (.97)
Inhibition (range: 0–1)	0.53 (0.24)
Vocabulary[a] (range: 0–45)	26.3 (9.48)
Movement behaviours[b]	
Sleep	11:42
Sedentary time	5:03
Light physical activity	5:38
Moderate-to-vigorous physical activity	1:37

[a] Vocabulary was limited to 711 participants as only 3 of 4 studies assessed this outcome

[b] Presented as compositional centre in hr:min. Calculated as the geometric means of each activity adjusted so that together all means sum to exactly 24 h

Results

The demographic characteristics of the sample are in Table 1. The mean age was 4.3 ± 0.7 years and 44.6% were girls. The geometric means indicate that sleep accounted for 48.7%, SED 21.0%, LPA 23.5%, and MVPA 6.7% of the 24-h day. The arithmetic means for the movement behaviours are in Table S3.

Associations between movement behaviours and cognitive function outcomes

Regression estimates for time spent in each movement behaviour relative to time spent in the remaining movement behaviours as they related to each of the cognitive function outcomes are shown in Table 2. The movement behaviour composition was significantly associated with working memory ($P = 0.03$) but not response inhibition ($P = 0.55$) or expressive vocabulary ($P = 0.44$). Relative time spent in sleep was negatively associated with working memory ($P = 0.01$), and relative time spent in SED was positively associated with working memory ($P = 0.01$). Relative time spent in the individual movement behaviours was not significantly associated with response inhibition or expressive vocabulary ($P > 0.2$).

Optimal time-use composition for individual cognitive function outcomes

Optimal time use was only determined for working memory since it was the only cognitive function outcome associated with the movement behaviours composition and/or at least one of the individual movement behaviours. Because optimal time use could only be determined for one outcome, we were not able to conduct the Goldilocks day analysis.

The centre (compositional mean) and range (min, max) of the set of predictive time-use compositions associated with the best 10% working memory scores were observed with 11:00 (9:00, 13:12) of sleep, 5:42 (5:12, 5:48) of SED, 5:06 (3:18, 6:30) of LPA, and 2:12 (1:18, 2:42) of MVPA.

Sensitivity analysis

Table S3 presents the compositional and the arithmetic mean of the movement behaviours when the accelerometer processing decisions for number of valid hours, number of valid days, and the cut-points used to distinguish different intensities of movement were changed. Table S4 presents the associations between the movement behaviour composition and cognitive function outcomes after these accelerometer processing decisions were changed. Table S5 shows the corresponding optimal time use values. When the valid day criterion was changed from ≥ 6 h to ≥ 8 h, the associations were comparable to those of the original analysis and the differences in optimal time use was ≤ 12 min/day for all movement behaviours When the number of valid days criterion was changed from ≥ 3 to ≥ 4 days, neither the composition nor the relative

Table 2 Compositional linear regression model estimates for cognitive function

	Model P value	Adjusted R^2 ilrs	Sleep, b (SE)	SED, b (SE)	LPA, b (SE)	MVPA, b (SE)
Working memory	0.03*	0.060	-0.423 (0.17)*	0.500 (0.21)*	-0.139 (0.26)	0.060 (0.15)
Response inhibition	0.55	0.053	-0.153 (0.15)	0.252 (0.19)	-0.070 (0.23)	-0.042 (0.14)
Vocabulary[a]	0.44	0.067	-0.144 (0.37)	0.179 (0.41)	-0.242 (0.33)	0.206 (0.14)

All estimates are adjusted for age, sex, parental education, parental marital status, and study. Adjusted R-squared for full models: working memory = 0.282, response inhibition = 0.388, Vocabulary = 0.458

Each regression coefficient and standard error [b (SE)] represents the association between the given outcome and the first z term of the correspondingly rotated behaviour composition

SED Sedentary behaviour, *LPA* Light physical activity, *MVPA* Moderate-to-vigorous physical activity

[*] Statistically significant results ($P < 0.05$)

[a] Analyses for the vocabulary outcomes was limited to 711 participants

time spent in sleep or SED were associated with working memory. Therefore, the optimal time use for working memory based on having at least ≥ 4 valid days of accelerometer data was not conducted. When the Trost et al. [54] cut-points were used in instead of the Evenson et al. [40] and Pate et al. [41] cut-points, the associations between the movement behaviour composition, individual movement behaviours, and the cognitive function outcomes were similar to those of the original analyses. However, the optimal time use was lower for LPA (-78 min/day) and higher for sleep (+ 36 min/day), SED (+ 30 min/day), and MVPA (+ 12 min/day).

Discussion

This study used CoDA to identify the optimal duration of sleep, SED, LPA, and MVPA related to measures of cognitive function in the early years. Working memory, but not the remaining cognitive function outcomes, was associated with the movement behaviour composition in this study. The best 10% working memory scores were observed with 11:00 (hr:min) of sleep, 5:42 of SED, 5:06 of LPA, and 2:12 of MVPA. Because working memory was the only cognitive function outcome associated with the movement behaviour composition, we were not able to perform the Goldilocks day analysis across all cognitive function outcomes.

We are aware of three previous studies that used CoDA to examine the association between the movement behaviour composition and cognitive functions in early years children. The first was conducted on a sample of 95 preschoolers with an average age of 4.5 years [17]. In that study, the movement behaviour composition was significantly associated with working memory and vocabulary but not response inhibition. Furthermore, relative time spent in SED was positively associated with vocabulary and response inhibition; associations were non-significant for sleep and PA. In the second study, which was conducted in a sample of 123 children aged 3 to 5 years, the 24-h movement behaviour composition was associated with overall executive functions [55]. That study did not report if the relative contribution of individual movement behaviours was associated with executive function [55]. The third study investigated how different combinations of PA, SED, and sleep affected cognitive functions in 135 children aged 3 to 5 years. It found that the overall 24-h movement behaviour composition was linked to executive function outcomes, with MVPA showing a positive correlation with cognitive flexibility [16]. Collectively, the mixture of significant and non-significant findings from the previous three studies and our study implies that associations between the 24-h movement behaviour composition and individual movement behaviours with cognitive outcomes are inconsistent. Because the methods and participant age ranges were comparable across these studies, the inconsistency in the results may be due to the small sample sizes which increase the likelihood of random sampling error. Small sample sizes can reduce the statistical power of the analysis, making it harder to detect true associations.

To our knowledge, ours is the first study to use the optimal time-use CoDA approach in a sample of early years children. Dumuid and colleagues used this approach in 11- to 12-year-olds and concluded that the optimal duration for movement behaviours varies substantially depending on the health outcome [27]. For example, the optimal durations for cognitive and academic outcomes were observed with 9:00 to 11:00 (hr:min) of sleep, 10:30 to 12:12 of SED, 1:42 to 2:30 of LPA, and 0:18 to 1:00 of MVPA [27]. The optimal time use values for these adolescents were very different from the values that we observed for working memory in early years children. Although this might reflect methodological differences in the way that these behaviours were measured, it seems that the early years children require far more LPA and MVPA and far less SED compared to 11–12-year-olds. The observed differences between age groups highlight that findings based on school-aged children and adolescents should not be generalized to early years children. This also supports current 24-h movement guidelines, as the guidelines for the early years recommend higher levels of PA and sleep than the guidelines for school-aged children and adolescents.

The optimal sleep duration range for working memory observed in our study was 9:00–13:12 h/min (compositional mean = 11:00 h:min). This is similar to the sleep duration range of 10–13 h/day recommended in the 24-h movement guidelines for the early years [20–23]. Furthermore, a similar proportion of our sample achieved the optimal sleep duration range for working memory (82.4%) and the sleep duration range recommended in the 24-h movement guidelines (74.7%). For physical activity, the optimal durations for total PA (7:18 h:min) and MVPA (2:12 h/min) that we observed for working memory were much higher than the minimum targets for total PA (≥ 3 h) and MVPA (≥ 1 h) recommended in the 24-h movement guidelines for the early years [20–23]. While > 97% of participants in our study accumulated enough physical activity to meet the 24-h movement guideline recommendations, only 43.1% and 4.7% accumulated more physical activity than the optimal value for total PA and MVPA, respectively. It was not possible to make a similar comparison between the optimal amount of SED and the recommendations provided in the 24-h movement guidelines because the latter only provides a specific recommendation for the screen time component of SED.

Some of the associations observed in our study were unexpected, particularly the positive association between SED and working memory, and the lack of significant associations between PA and all cognitive function measures. The positive association for SED may reflect that certain sedentary activities, such as reading and storytelling, likely have beneficial effects on cognitive function [6]. The null associations for PA may reflect that the traditional accelerometer processing methods used in our study may not effectively capture the full range of movement intensity in children, especially high-frequency movements [56]. On the other hand, research indicates that different domains of cognitive function such as working memory and response inhibition develop at different age stages, which may influence their responsiveness to movement behaviours. Studies showed that working memory may develop more rapidly than response inhibition in early years [57, 58]. For example, preschoolers can engage in tasks that require holding information temporarily (working memory) but they often struggle with tasks that need inhibiting responses or distractions [57, 58]. Therefore, these differences in the developmental trajectories could explain why movement behaviours may be associated with working memory but not with other cognitive measures.

Results from Goldilocks day analyses could be used to develop more personalized recommendations for children based on their specific circumstances and health goals. For example, optimal movement behaviour levels for a specific health outcome could be targeted rather than movement behaviour levels that will provide some health benefits for a variety of health outcomes. It can guide researchers, policymakers, and caregivers towards creating environments and routines that support optimal health and cognitive function during this crucial stage of life. Furthermore, results from the present study, along with others employing similar methodologies, could inform future updates to the 24-h Movement Guidelines.

Strengths of this study include the use of a large sample from four countries with objective 24-h device-based measurements and validated cognitive function scores. In addition, we performed sensitivity analyses that showed similar results across a range of scenarios which confirms that the patterns are robust. However, the study is limited by its cross-sectional study design and its inability to make causal inferences. Although some of the individual studies that contributed to SADEY used a cluster sample approach (i.e., children were clustered by childcare centre), this clustering information was not available in the SADEY database and was not accounted for in our analyses. In addition, there were some missing potential confounders such as race/ethnicity and children's motor or learning difficulties. Furthermore, we did not consider different types or contexts (e.g., solitary vs group, indoors vs outdoors, screen vs non-screen) of SED or PA, nor the distinguishment between naps and nighttime sleep. In addition, the process we used to normalize the day so that time spent in all movement behaviours added to exactly 24-h excluded sleep, which may have impacted the results. Finally, we could only examine the composition within our sample footprint, and it is possible that the optimal composition falls outside of this footprint.

In conclusion, of the cognitive outcomes assessed, only working memory was associated with the movement behaviour composition. The best working memory scores were observed with 11:00 (hr:min) of sleep, 5:42 of SED, 5:06 of LPA, and 2:12 of MVPA. Future research should consider partitioning intensities in different ways (e.g., portioning naps from nighttime sleep, light physical activity into low light physical activity and high light physical activity, and moderate from vigorous physical activity). Additional research with larger sample sizes that uses similar CoDA methods across a variety of health and cognitive function outcomes is needed to gain a better understanding of how much sleep, SED, and PA are needed to achieve the best health in the early years. Such research could inform future updates to the 24-h movement guidelines.

Abbreviations

PA	Physical activity
SED	Sedentary behaviour
LPA	Light physical activity
MVPA	Moderate-to-vigorous physical activity
CoDA	Compositional data analysis
SADEY	Sleep and Activity Database for the Early Years
EYT	Early Years Toolbox

Supplementary Information

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Supplementary Material 1.

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Authors' contributions

IJ and SZ came up with the idea of this study. DC and JB were responsible for collecting data for BATH-ABC study. AO and SR were responsible for collecting data for Jump-Start study. EA andKA DC were responsible for collecting data for ACTNOW study. VC was responsible for collecting data for Prox-dev study. DV was responsible for data curation. IJ was responsible for conceptualisation, methodology, supervision of the study and review and editing of the manuscript. DD was responsible for conceptualisation, methodology. SZ was responsible for formal analysis, methodology, and writing the original draft of the manuscript. All authors were responsible for review and to provide critical feedback. All authors approved the final text and had final responsibility for the decision to submit the manuscript for publication.

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Data availability

Data were obtained from the Sleep and Activity Database for the Early Years (SADEY), which is a consortium of pooled accelerometer-measured movement behaviour data in children aged 6 years or younger. The SADEY database is available upon application and with restrictions. Further details regarding data access can be found at https://www.uow.edu.au/global-challenges/living-well-longer/early-years-accelerometry/.
No datasets were generated during the current study.

Declarations

Ethics approval and consent to participate

The SADEY project was approved by the University of Wollongong Health and Medical Human Research Ethics Committee (2021/249) [28]. The studies included in this study were also ethically approved as follows: ACTNOW—Institutional Ethics Committee and the Norwegian Centre for Research Data—#248220; Jump Start—University of Wollongong Human Research Ethics Committee (HE14/137); PATH ABC—University of Wollongong Health and Medical Human Research Ethics Committee—#HE14/310); PROXDEV—University of Alberta Human Research Ethics Board (00081175).

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

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