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Association between objectively measured, multidimensional sleep health and cognitive function in older adults: cross-sectional wearable tracker study

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ABSTRACT

Both sleep and cognition are multidimensional constructs. Using univariate methods to examine associations between sleep and cognition may inadequately characterize the association between these arrays of variables. The current study used a multivariate approach to identify key sleep metrics and cognitive domains contributing to the maximum sleep-cognition covariance in healthy older adults. In 773 community-dwelling older adults of ages 65–80 years, sleep was assessed using the Oura Ring worn for 15–28 days. Cognition performance in seven domains was assessed using standardized tests. The overall covariance between sleep and cognition was examined by a partial least square correlation (PLSC) analysis. Sleep metrics and cognitive domains contributing to significant PLSC components were identified by bootstrapping. PLSC analysis identified a component that explained 82 % of covariance between sleep and cognition matrices ($r = 0.2$, $p < 0.001$). Bootstrapping tests further identified 11 sleep continuity and regularity metrics and 3 corresponding cognitive domains that contributed significantly to the observed covariance. Post-hoc univariate analyses showed that sleep continuity metrics correlated with speed of processing, while sleep regularity metrics correlated with verbal memory, executive functions, and speed of processing. Our results suggest that sleep continuity and regularity may be more sensitive markers of impairments across multiple cognitive domains in healthy aging compared to sleep duration and timing.

1. Introduction

The importance of sleep as a factor associated with cognitive performance in older adults has been widely recognized [1]. To date, most research on sleep and cognition has focused on univariate correlations between specific sleep measures and cognitive function, for example, relating sleep duration to memory performance. However, both sleep and cognition are multidimensional constructs [2,3]. Quantifying the overall correlation strength between sleep and cognition reveals the extent to which sleep influences cognitive functions in the ageing population. Clarifying the associations between various sleep metrics and different cognitive domains could refine our understanding of the factors underlying age-related cognitive impairment.

Sleep timing, duration, continuity, satisfaction, daytime alertness, and regularity are components of 'healthy sleep' [2]. Many past studies on sleep and cognition in older adults assessed only sleep duration using questionnaires [4,5]. Both long and short sleep durations assessed in this manner, have been associated with poorer cognition [6] and an increased risk of cognitive impairment and dementia [7–9]. However, when sleep was assessed objectively via polysomnography or actigraphy, the association between duration and cognition in older adults appears less consistent [10].

Population health studies on sleep and cognition involving older adults often assess cognition in a single domain [11] or use simplified

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brief assessments of global cognition like the Mini-Mental State Examination (MMSE) [12,13]. A recent meta-analysis found that poorer sleep continuity was associated with worse memory performance in older adults [14]. However, this meta-analysis aggregated results from both subjective and objective sleep studies. The association between sleep continuity and memory performance was not replicated in objective sleep studies with large sample sizes [15,16].

Most of these studies employed a univariate approach to examine hypothesized correlations between one sleep metric (e.g., duration) and a cognitive domain (e.g., memory). A single sleep measure (e.g., sleep duration) provides a limited depiction of an individual's sleep habit. Similarly, scores from a brief assessment of global cognition provides a coarse assessment of cognitive function. Hence, results from univariate analyses, provide a limited perspective of the multidimensional associations between sleep and cognition.

A recent systematic review and meta-analysis on the associations between objectively measured sleep metrics and cognitive domains in older adults found that most included studies had small sample sizes and short recording periods (less than 7 nights), which may not accurately reflect habitual sleep patterns [10]. While some large cohort studies incorporated comprehensive sleep and cognitive assessments, they had mainly used univariate analytic approaches where multicollinearity among variables and multiple testing are problematic [11,16,17]. The overall strength of association between sleep and cognition from this meta-analysis was weak ($r = 0.1$) and inconsistent due to high heterogeneity among studies. Moreover, results were not definitive on the mapping of multidimensional sleep measures to their related cognitive domains [10].

In the current study, we employed a multivariate method to examine the overall correlation between sleep and cognition and identify key sleep metrics and cognitive domains. We analyzed data from community-based older Chinese adults in Singapore, who underwent assessment for multiple habitual sleep parameters using a smart ring tracker (Oura Ring) and were examined for cognitive functions in multiple domains.

Specifically, the current study aimed to 1) estimate the overall strength of the sleep-cognition association and 2) identify the key sleep metrics and cognitive domains contributing to the overall correlation.

2. Methods

2.1. Study design

We used data from the SG70 project, which is nested in the Singapore Chinese Health Study (SCHS) [18]. The SG70 study, which started in September 2021, aimed to recruit about 1200 surviving participants aged 65–80 from the SCHS cohort and was designed to comprehensively assess ageing outcomes and associated factors. All participants gave informed consent, and this study was approved by the Institutional Review Board of the National University of Singapore.

The SG70 study included three home visits by trained interviewers to collect data from each participant using structured questionnaires, which included the Singapore-modified MMSE [19], and questions about sleep and naps via the Sleep Health Index (SHI) [20]. Participants were also invited to wear the Oura ring for up to 4 weeks (28 days), with instructions to wear the ring all the time, except for shower, during which the rings should be charged. After the home visits, usually within two to four months, consenting participants were invited to visit the SG70 Centre and other related facilities at the National University of Singapore to undergo assessment using standardized cognitive tests, physical measurements, and different imaging modalities for the evaluation of ageing outcomes in different systems and organs.

As of March 2025, 1101 participants from the SG70 cohort had completed a comprehensive measure of ageing outcomes in different dimensions, including physical, cognitive, psychological, and social dimensions. The current analysis focused on 773 participants who had worn the Oura ring for more than 14 days and had complete neuropsychological assessment data.

2.2. Primary measures

2.2.1. Sleep assessment

Participants were requested to charge, wear, and sync the Oura Ring (Oura Health OY, Oulu, Finland) daily to track sleep and physical activity for up to 4 weeks. The accuracy of Oura ring in detecting sleep and wake activities has been validated against the gold standard Polysomnography by many independent research groups [21–26]. Most importantly, Oura's accuracy has been validated explicitly in local Singaporean samples with a wide age range (21–70 years) [22,23,26].

Only periods labeled as "Sleep" by Oura were examined and analyzed in the current study. For any given day, the sleep period with the longest total sleep time between 1800h the previous day and 1759h that day was considered the main sleep period. Any other sleep period was classified as a nap. Checks were made to accurately characterize the diversity of sleep patterns under free-living conditions, especially irregular or short sleep (including days without sleep). Non-wear periods were accounted for while collecting this data (see Supplementary Material).

A total of 23 sleep metrics were examined in the current analyses: 20 were extracted directly from Oura's provided data (Fig. 1; Supplementary material), and three were calculated based on Oura sleep and activity data (sleep regularity index, SRI; sleep fragmentation index, SFI; and SFI standard deviation). The SRI quantified whether an individual was in the same arousal state (awake or asleep) 24h apart [27]. SRI ranged between 0 and 100, with 100 meaning an individual was always in the same arousal state at the same time every day (Supplementary Material). The SFI quantified sleep disturbance during the main sleep period as the sum of a Movement Index (percentage of TIB with movement) and a Fragmentation Index (percentage of sleep lasting ≤1min) [28,29].

2.2.2. Cognitive assessment

Cognitive performance was assessed during the first two center visits, 7–10 days apart. A total of 10 standardized cognitive tests spanning seven cognitive domains were administered. Verbal Learning and Memory were assessed with the Rey Auditory Verbal Learning Test [30,31]. Language was assessed with a modified Boston Naming Test. Visual Memory was assessed with the Paired Associative Learning test in

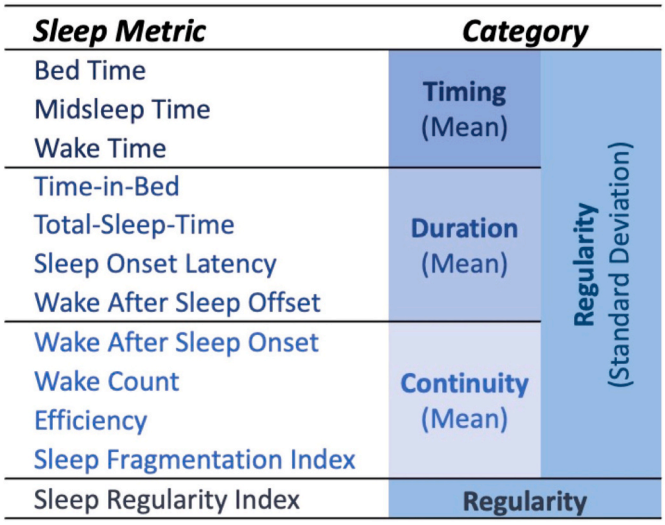

Fig. 1. Sleep metrics from Oura. A total of 23 sleep metrics were derived from Oura data, and grouped into 4 categories: Timing, Duration, Continuity and Regularity.

CANTAB and the Brief Visuospatial Memory Test-Revised (BVMT-R) [32]. Executive function was assessed with the Colour Trail Test 2 [33] and the Design Fluency Test [34]. Attention was assessed with WAIS-III forward and backward Digit Span. Visuospatial ability was assessed with the WAIS-III Block Design [35]. Processing speed was assessed with the Color Trail Test 1 [33] and the written and oral scores from the Symbol Digit Modality Test [36]. Tests were administered in either English or Mandarin according to the participant's language preference and proficiency.

Scores of each test were first standardized to T scores with a mean of 50 and a standard deviation of 10. Response times from the Colour Trail Tests were inverted prior to standardization such that a larger value indicated better performance. Scores in cognitive domains covered by more than one test were the mean of all that domain's test scores.

2.2.3. Assessments of covariates

During the first home visit, overall cognitive status was assessed using the Singapore-modified MMSE. Depressive symptoms were assessed with the 15-item Geriatric Depression Scale (GDS) [37]. Functional status was assessed using the Lawton-Brody Instrumental Activities of Daily Living Scale (IADL) [38]. Height and weight were measured using standard scales to calculate body mass index (BMI) at the first centre visit. History of chronic disease(s) (e.g., hypertension, diabetes, and stroke) and smoking status were self-reported. Subjective sleep and napping experiences were assessed via the SHI. Sleep disorders were not objectively identified; however, participants were specifically asked in the SHI if they have been diagnosed with insomnia or sleep apnea. The SHI also asked participants whether they were taking medication or supplements for sleep.

2.3. Statistical analysis

2.3.1. Partial least squares correlation to assess overall sleep-cognition correlation

Influences of potential confounding variables (i.e., age, sex, years of education, depressive symptoms, chronic diseases, smoking status, BMI, and sleep disorders) were removed from both sleep and cognition metrics by linear regressions. The resulting matrices of sleep and cognition were then entered into a partial least square correlation (PLSC) analysis to calculate the maximum covariance between sleep and cognition.

PLSC [39–41] analysis is a multivariate statistical technique employed to identify optimal relationships between two matrices (i.e., sleep and cognition). The PLS method offers several advantages. First, it allows for the exploration of potential structures in modeling the covariance between channels, in addition to their mean effects. Second, compared to univariate statistics, PLS does not require multiple comparison correction since it only involves a single test to evaluate the statistical significance of the multivariate pattern against a null distribution. A third advantage of the PLS approach lies in its data-driven nature, which minimizes the impact of individual researcher decisions. Our PLS analysis began with a covariance matrix between cognitive scores from 7 domains, and 23 sleep metrics derived from Oura data. Then, the covariance matrix underwent a singular value decomposition (SVD), yielding orthogonal latent variables (LVs) that explained the maximal covariance between cognitive and sleep variables. Generally, the number of variables in the smaller matrix (i.e., cognition matrix) equals the number of LVs. Each LV consisted of three parts: 1) a singular value representing the sleep-cognition covariance explained by this LV, 2) the singular vector of sleep saliences (sleep scores), and 3) the singular vector of cognitive saliences (cognitive scores). The direct correlation value (Pearson's r) between the sleep scores and the cognitive scores then quantified the sleep-cognition relationship identified by a particular LV.

The significance of each LV was evaluated using 5000 permutation tests. A LV was deemed significant if the observed singular value was greater than the permuted singular value in more than 95 % of the permutations (permuted $p < 0.05$).

2.3.2. Bootstrap test to identify important sleep and cognition metrics

For each significant LV, the reliability of sleep and cognitive scores was evaluated using 5000 bootstrap tests to identify individual metrics that made the most robust contributions. A bootstrap ratio (BSR), as a normalized estimate of robustness, was calculated by dividing each metric's mean salience by its bootstrapped standard error. Sleep and cognitive metrics exhibiting a BSR of +2 or higher were deemed significant, equivalent to a 95 % confidence level. PLSC analysis was conducted using the ExPosition package in R.

The reproducibility and reliability of the PLSC results were tested through split-half and test-train methods. Details of the permutation tests and codes can be found in the Supplementary Material. The methods were derived based on a recent preprint and GitHub page [42].

2.3.3. Post-hoc partial correlation to clarify specific correlations between sleep and cognition metrics

To identify specific sleep-cognitive pairings, we also conducted post-hoc univariate partial correlation analyses between sleep and cognitive metrics with BSR over 2 from significant PLSC LVs. Correction for multiple comparisons was not performed for the post-hoc analysis because the significance of the sleep-cognition correlation was already established via the PLSC analysis.

3. Results

3.1. Participant characteristics

The final analysis sample included 773 older adults (Fig. 2) with both complete cognitive assessment and more than 14 days of Oura data. Table 1 presents their demographic information. With a mean age of 73.4 years, the participants in our study were older than those in other sleep-ageing studies [10]. Additionally, our study participants were not as highly educated as those from most ageing studies conducted in North America and Europe [10]. The wide ranges of sleep duration and sleep efficiency showed that our study included both healthy and unhealthy sleepers. Raw scores for the 10 cognitive tasks were presented in supplementary material.

Using the Singapore-modified MMSE, most of the 773 participants were cognitively intact (mean score = 27), and only 9 participants had scores <21, often used as the cutoff for cognitive impairment in East Asian studies. The mean GDS score was 1.6 out of 15, and the mean IADL score was 7 out of 8. Further, for medical history, 469 (60 %) reported hypertension, 192 (25 %) reported diabetes, 128 (17 %) reported coronary heart disease or heart failure, 31 (4 %) reported stroke, and 15 (2 %) reported kidney disease. Sixty-two participants reported having sleep disorders such as insomnia or sleep apnea or taking sleep medication. There was no shift worker in the study.

3.2. PLSC results

3.2.1. Overall sleep-cognition correlation

The PLSC analysis identified one pair of latent variables contributing to 82 % of covariance between sleep and cognition ($p < 0.001$; Fig. 3A). The correlation between sleep score and cognition score from this component was at $r = 0.2$ ($p < 0.001$; Fig. 3B). Removing the 9 participants with low MMSE scores did not change the PLSC results (Supplementary Material). Participants (N = 62) with self-reported sleep disorder or taking medication/supplements for sleep did not have worse cognitive status (MMSE = 27.7) than the others (MMSE = 27.2). Removing these participants also did not change the overall sleep-cognition association (Supplementary Material).

3.2.2. Important sleep and cognition metrics identified by bootstrapping

The bootstrapping test showed that 11 out of the 23 sleep metrics had

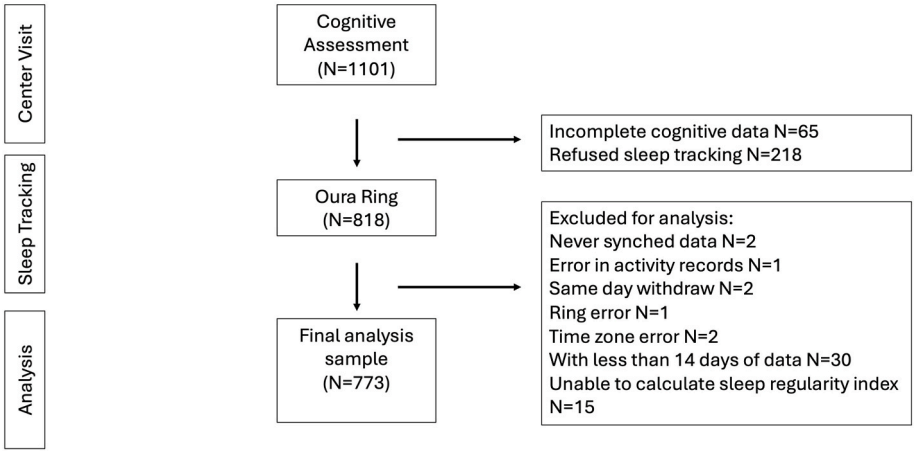

Fig. 2. Consort diagram showing the flow of SG70 participants that were included in the current analysis.

Table 1
Demographic and sleep characteristics of SG70 participants with cognitive scores and more than 14 days of Oura data (N = 773; 395 females).

	Mean	Median	Range
Age at SG70 recruitment	74.5	74.3	67–80
Years of education	10.1	11.0	0–19
Singapore-modified MMSE score	27.2	28	17–30
15-item GDS score	1.6	1	0–14
Lawton IADL score	7	8	3–8
BMI (kg/m^2)	23.6	23.8	13–44
Average time in bed (hr)	7.5	7.6	4–11
Average total sleep time (hr)	6.1	6.1	2–9
Average WASO (min)	59.7	53.4	11.2–208
Average sleep efficiency (%)	80.8	81.8	48–93
Average bedtime	11:16 p.m.	11:13 p.m.	6pm-6am
iSD of time in bed (hr)	1.0	1.0	0.2–3.8
iSD of total sleep time (hr)	0.9	0.9	0.2–3.2
iSD of WASO (min)	32.8	30.1	6.9–88.3
iSD of sleep efficiency (%)	6	5.8	1.8–17.6
iSD of bedtime (min)	61.5	53.6	4–343

Note. MMSE = Mini-Mental State Examination; GDS=Geriatric Depression Scale; IADL= Lawton-Brody Instrumental Activities of Daily Living Scale; BMI=Body Mass Index; iSD = intraindividual standard deviation; WASO= Wake After Sleep Onset.

a robust contribution (BSR ratio >2) to the dominant component: 3 metrics of sleep continuity and 8 metrics of sleep regularity (Fig. 3C). None of the sleep duration or timing metrics contributed to this component. Three out of seven cognitive domains contributed to this component: verbal memory, executive functions, and processing speed. In general, older adults with more continuous and regular sleep patterns also performed better in these three cognitive domains.

To examine the potentially quadratic relationship between sleep duration and cognitive functions, a separate PLSC analysis was run with squared values of time in bed and total sleep time. This additional analysis showed that squared sleep duration measures also did not contribute to the dominant component (Supplementary Material).

Permutation tests were conducted to determine the reliability and reproducibility of current PLSC results. The results of these procedures showed that the first component was significantly reliable and reproducible (Supplementary Material).

3.2.3. Post-hoc univariate analysis to clarify specific sleep-cognition correlations

The PLSC analysis identified a reduced set of 11 sleep metrics and 3 cognitive domains contributing to the overall correlation. However, it could not specify exactly which sleep metric was associated with which cognitive domain or whether a sleep metric was associated with multiple domains. Therefore, a partial correlation analysis was conducted on the reduced sleep and cognition variables (Fig. 4A). This reduced correlation test showed an overall pattern of weak correlation coefficients between sleep and cognition variables ($|r| = 0.05$–0.17).

Sleep continuity metrics are correlated with speed of processing. Sleep regularity metrics, especially the sleep regularity index (SRI), correlated with verbal memory, executive function, and processing speed. Sleep regularity carries more information about one's habitual sleep than the average duration across days, as depicted in Fig. 4B. The highest correlation coefficient was found between SRI and executive function ($r = 0.17$).

4. Discussion

To our knowledge, this is the first empirical study examining the overall correlation between multidimensional sleep and cognition in community-dwelling older adults using a multivariate approach. With a relatively large sample size, reliable long-term objective sleep tracking with a locally validated device, and comprehensive cognitive assessment, we found a significant overall correlation between sleep and cognition in this representative community-sourced sample of older adults ($r = 0.2$). Measures of sleep continuity and regularity, but not timing and duration, contributed significantly to the overall sleep-cognition relationship. Specifically, high sleep regularity was associated with better memory, executive functions, and processing speed, while high sleep continuity was associated with better processing speed.

Previous studies examining the correlation between sleep and cognition mostly employed univariate approaches, such as multiple correlations and regressions. While effective in hypothesis testing, these approaches preclude estimation of the overall correlation between two multidimensional constructs (i.e., sleep and cognition). The current study used a multivariate method (PLSC) to examine matrix-to-matrix correlations between sleep and cognition. With long-term (>14 days) sleep tracking in a large (>700) and representative cohort, our results represent an advance relative to past studies with temporally less dense sampling and univariate methodology.

The first aim of the current study was to quantify the overall correlation between multidimensional sleep and cognition in older adults. Our results show that the correlation strength between sleep and cognition in community-dwelling older adults was at $r = 0.2$. A correlation coefficient of 0.2 may seem weak. Nevertheless, it was comparable to the correlations between cognition and other age-related cognitive impairment risk factors with similarly large sample sizes [43–45]. While studies with large sample sizes are powerful in characterizing the population effects, large individual differences among participants influenced the correlation strengths. The small but similar

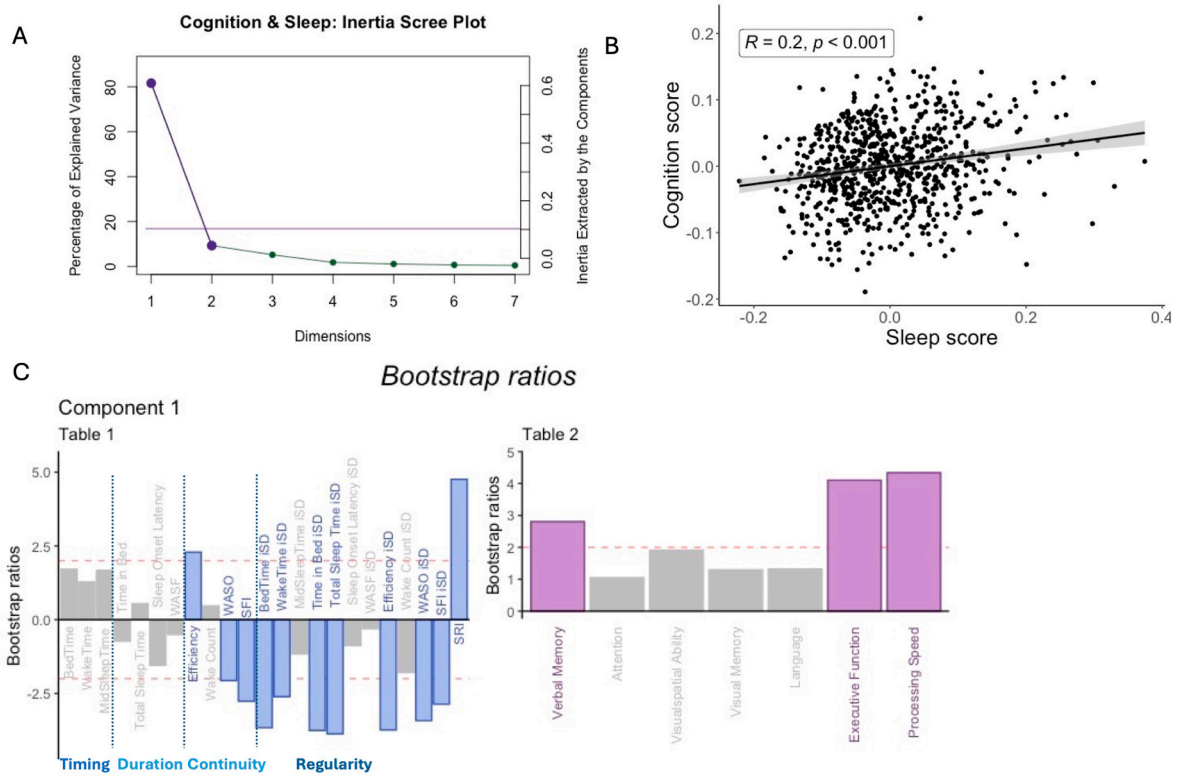

Fig. 3. Results from the PLSC analysis. **A.** Scree plot showing there was one significant component that explained 82 % of covariance between sleep and cognition. **B.** Scatter plot showing the correlation between sleep scores (latent variable X) and cognition scores (latent variable Y) obtained from the significant first PLSC component. **C.** Bar plot showing results from bootstrapping. Only metrics that had robust contributions to the first component were colored. Table 1 presents the sleep metrics and Table 2 presents the cognitive domains. Direction of bars indicates direction of association. In general, higher sleep continuity and regularity was associated with better verbal memory, executive functions, and processing speed. WASO = wake after sleep onset; SFI = sleep fragmentation index; SRI = sleep regularity index; iSD = intraindividual standard deviation.

coefficients across factors suggest multiple physiological mechanisms underlying cognition, with each factor (e.g., sleep and brain volume) playing a small but significant role.

The PLSC method also enabled us to address our second aim, which was to identify important sleep metrics and cognitive domains that contributed to the overall correlation. By bootstrapping tests, 11 sleep metrics and 3 cognitive domains were identified, down from the original 23 sleep metrics and 7 cognitive domains. The 11 key sleep metrics were all from sleep continuity and regularity measures. The three cognitive domains: memory, executive functions, and processing speed, were from the family of fluid cognition measures with the most drastic decline with ageing [46]. Our results suggest that sleep continuity and regularity are the most relevant sleep metrics that correlate with performance in fluid cognitive functions.

The reduced sets of sleep metrics and cognitive domains from the PLSC analysis facilitated targeted univariate analyses to explore the specific correlations between key sleep metrics (continuity and regularity) and fluid cognitive domains. Partial correlations show that sleep continuity was associated with processing speed, consistent with two other public health studies [15,16]. Based on these findings, fragmented sleep might specifically impact processing speed in older adults.

Most importantly, sleep regularity measures, especially the sleep regularity index (SRI), were correlated with all 3 fluid cognitive domains. The correlation strength between SRI and executive function was the strongest among univariate analyses (r = 0.17). Sleep regularity measures carry more information about one's habitual sleep than average duration [47]. Two participants with similar average durations could have drastically different sleep/wake patterns across multi-day measurement periods (Fig. 4B). Recent reviews and empirical studies have highlighted the importance of regular sleep on physical health and dementia risk in older adults [48], and the need for more studies focusing on sleep regularity [47,49]. Our findings provide further evidence that sleep regularity plays an important role in cognitive ageing, especially in executive functions. Future studies should investigate the underlying neural mechanisms linking sleep irregularity and age-related impairments of executive functions.

The SRI itself can be viewed as a multidimensional metric. It is calculated by comparing consecutive nights. Therefore, sleep metrics, such as duration continuity and timing, contribute to the calculation of SRI. The SRI can only be calculated across days, thus considering the intraindividual variations in multiple sleep metrics. The multidimensional nature of SRI could explain its correlation with multiple cognitive domains.

The SRI can now be readily monitored, non-invasively and passively, in the general population via widely available wearable trackers. Moreover, irregular sleep/wake patterns have been associated with other risk factors, such as small brain volume and high cardiovascular risks [49]. It is unclear how sleep regularity interacts with other risk factors that influence cognitive functions in ageing. Longitudinal change in sleep regularity with normal or pathological ageing has not been clearly characterized. Prioritizing sleep regularity measures in future ageing and sleep research may offer more significant insight into age-related cognitive impairment.

Although we controlled for factors associated with sleep apnea, such as BMI, smoking, chronic diseases, and self-reported sleep disorders, we did not obtain objective measures of obstructive sleep apnea (OSA). OSA is highly prevalent in older adults [50]. The rate of undiagnosed OSA in the general population is believed to be high, especially in Asian populations [51]. There are clear associations between OSA and cognitive impairment in older adults [52]. Therefore, undiagnosed OSA could

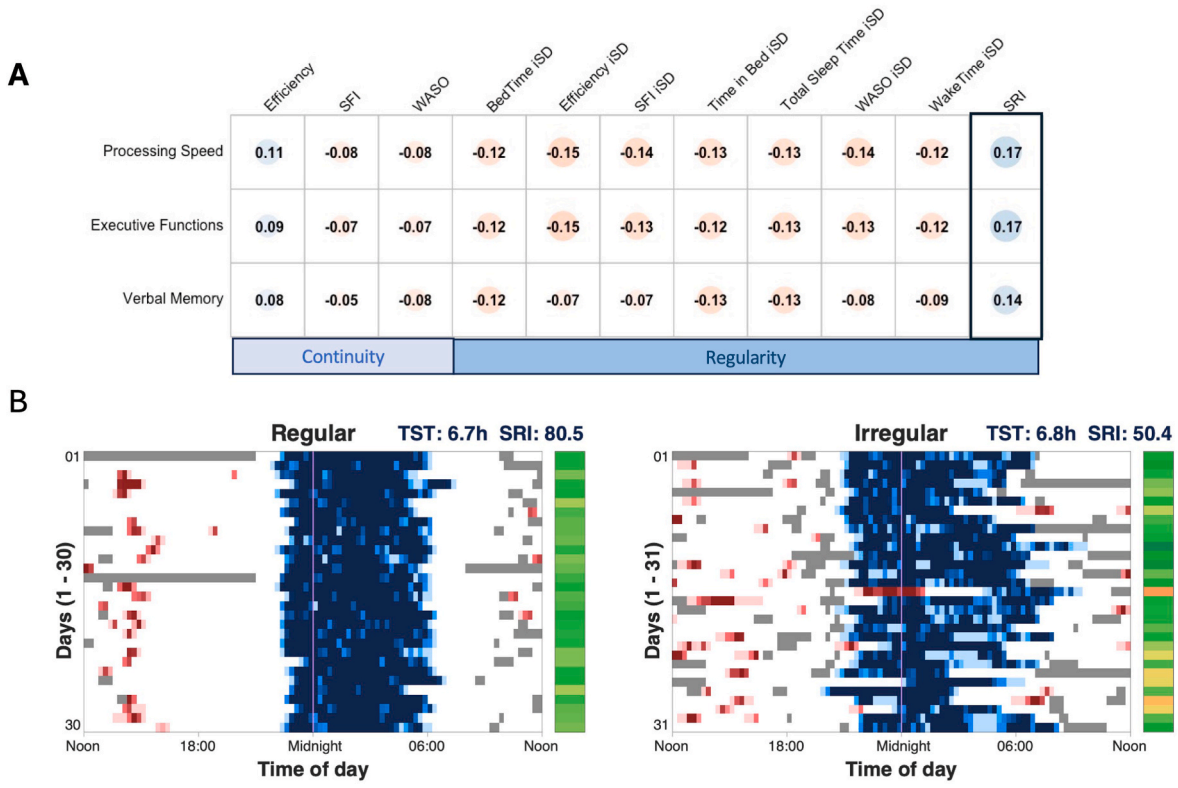

Fig. 4. A. Heat map showing partial correlation results between the 11 sleep metrics and 3 cognitive domains that contributed to the significant PLSC component. Numbers are correlation coefficients from partial correlation analyses between sleep metrics and cognitive domains, controlling for covariates. Note all coefficients are smaller than 0.2. Color density (−0.8-0.8) and size of the circle also reflect correlation strength. Blackbox highlights the correlations between SRI and all three cognitive domains. **B.** Sleep probability plots of two SG70 participants with similar average sleep durations (7 h) but very different SRI. Each line in the sleep probability plot represents a 24-h day for this participant from Oura ring. Blue epochs are times when the participant is sleeping. Red epochs are times when the participant is napping. Grey epochs are non-wear time. Green bars on the side present total sleep time (TST) of each 24-h period. WASO = wake after sleep onset; SFI = sleep fragmentation index; SRI = sleep regularity index; iSD = intraindividual standard deviation. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

have influenced the current results.

It is important to note that the current study was not designed to examine any specific theory about sleep and cognition. Numerous studies have investigated the relationship between specific cognitive domains and sleep, such as memory consolidation and slow-wave sleep [53]. However, these results often fail to replicate in different samples or under different conditions [54]. A recent meta-analysis found no consistent association between memory and slow-wave sleep in older adults [10]. We argue that a set of sleep metrics reliably and robustly associated with cognition needs to be identified using large cohort studies before we can derive or examine any theory for sleep and cognition in ageing. The current study, with its exploratory nature, was designed precisely to identify such sleep metrics.

One major limitation of the current study was the restricted age range in our sample. As part of the follow-up to the SCHS, the average age of participants in the current sample was 73, with a range between 65 and 80. There was no participant aged between 60 and 65, which constitutes a larger portion of the ageing population. Our results only characterized habitual sleep patterns and their correlations with cognition in those who lived longer and, therefore, may be influenced by survival bias. Another limitation was the lack of subjective sleep diary data to corroborate objective sleep patterns recorded by Oura ring. Some individuals with erratic sleep patterns may not be measured correctly.

In conclusion, we found that multidimensional sleep health was significantly associated with cognition in community-dwelling older adults. This association was driven by measures of sleep continuity and regularity and their correlations with fluid cognitive domains. Most importantly, sleep regularity index was correlated with multiple cognitive domains. Future studies should focus on investigating the possibly mechanisms linking sleep regularity to cognitive functions in older adults.

CRediT authorship contribution statement

Shuo Qin: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization. **Eric Kwun Kei Ng:** Writing – review & editing, Methodology, Formal analysis, Conceptualization. **Chun Siong Soon:** Writing – review & editing, Visualization, Methodology, Data curation, Conceptualization. **Xin Yu Chua:** Visualization, Data curation. **Juan Helen Zhou:** Writing – review & editing, Supervision, Resources, Methodology, Investigation, Conceptualization. **Woon-Puay Koh:** Writing – review & editing, Supervision, Resources, Project administration, Investigation, Funding acquisition, Conceptualization. **Michael Wei Liang Chee:** Writing – review & editing, Supervision, Resources, Methodology, Investigation, Funding acquisition, Conceptualization.

Data availability

The analytic methods and codes for analysis are available upon request. To enquire about the SG70 dataset, please email Dr. Woon-Puay Koh: kwp@nus.edu.sg.

Declaration of competing interest

The authors declare the following financial interests/personal

relationships which may be considered as potential competing interests:

Professor Michael Wei Liang Chee is a member of the Medical Advisory Board of Oura Health. All other authors have nothing to disclose.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.sleep.2025.106569.

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