Six multidimensional sleep health facets in older adults identified with factor analysis of actigraphy: Results from the Einstein Aging Study

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A B S T R A C T

Objectives: The concept of multi-dimensional sleep health, originally based on self-report, was recently extended to actigraphy in older adults, yielding five components, but without a hypothesized rhythmicity factor. The current study extends prior work using a sample of older adults with a longer period of actigraphy follow-up, which may facilitate observation of the rhythmicity factor.

Methods: Wrist actigraphy measures of participants (N = 289, M age = 77.2 years, 67% females; 47% White, 40% Black, 13% Hispanic/Others) over 2 weeks were used in exploratory factor analysis to determine factor structures, followed by confirmatory factor analysis on a different subsample. The utility of this approach was demonstrated by associations with global cognitive performance (Montreal Cognitive Assessment).

Results: Exploratory factor analysis identified six factors: Regularity: standard deviations of four sleep measures; midpoint, sleep onset time, night total sleep time (TST), and 24-hour TST; Alertness/Sleepiness (daytime): amplitude, napping (mins and #/day); Timing: sleep onset, midpoint, wake-time (of nighttime sleep); up-mesor, acrophase, down-mesor; Efficiency: sleep maintenance efficiency, wake after sleep onset; Duration: night rest interval(s), night TST, 24-hour rest interval(s), 24-hour TST; Rhythmicity (pattern across days): mesor, alpha, and minimum. Greater sleep efficiency was associated with better Montreal Cognitive Assessment performance (β [95% confidence interval] = 0.63 [0.19, 1.08]).

Conclusions: Actigraphic records over 2 weeks revealed that Rhythmicity may be an independent factor in sleep health. Facets of sleep health can facilitate dimension reduction, be considered predictors of health outcomes, and be potential targets for sleep interventions.

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Introduction

Appreciation for the nuances of sleep health has grown with time. The concept of sleep deficiency was initially defined in 2011 as insufficient sleep duration and/or inadequate sleep quality. This overarching definition, although conceptually useful for relating sleep to health and well-being outcomes, oversimplifies the analytical and conceptual complexity of distinguishing those measures. Positively framed health promotion can often be more effective than negative framing, as with “sleep deficiency.”

In contrast to sleep deficiency, the RU-SATED model proposed in 2014 defines six self-reported sleep health “dimensions”: Regularity, Satisfaction with sleep; Alertness during waking hours; Timing of sleep; Sleep efficiency; and Sleep duration. The RU-SATED model has demonstrated predictive value for health outcomes including mental health and all-cause mortality. RU-SATED may therefore be a useful tool for promoting healthy aging.

Later extensions of the RU-SATED model identified a five-dimension structure defining sleep health, including Timing, Efficiency, Duration, Alertness/Sleepiness, and Rhythmicity, using a factor analysis (FA) approach that included device-derived data from samples of older adults. A sixth factor, Rhythmicity, describing rhythmic diurnal patterns of sleep and wake, was also hypothesized but was not identified, potentially due to the relatively brief...
recording duration (4-5 days). Among a total of the 310 participants assessed between May 2017 and February 2020, 296 provided actigraphy data. Seven of these were excluded from the analysis because they did not provide a minimum of 7 days of valid actigraphy records. The final sample size for this analysis is thus 289 individuals who provided an average of 15.6 valid days (median of 16 days, range of 7-16 days) of actigraphy.

**Actigraphy processing**

Sleep actigraphy measures were collected with an accelerometer (Actiwatch Spectrum Plus; Philips-Respironics, Murrysville, PA) worn on the non-dominant wrist for 16 days, and downloaded with Philips Actiware software (version 6.0.4). Two independent scorers determined the daily cut-point, validity of days, and set sleep intervals using a previously validated algorithm without using information from a sleep diary. The scorers adjudicated each recording for inter-rater agreement by verifying the number of valid days, cut-point, number of sleep intervals, and differences greater than 15 minute in duration and wake-after-sleep-onset for each sleep interval. A sleep actigraphy day was determined invalid and no sleep interval was set if there were ≥4 total hours of off-wrist time, except for the first and last study day, constant false activity due to battery failure, data unable to be recovered, or an off-wrist period of ≥60 minute within 10 minute of the scored beginning or end of a night sleep period. Sleep intervals, including naps, were scored if the duration was at least 20 minutes.

During data processing, nighttime actigraphic sleep measures were calculated on the longest sleep duration interval that overlapped 10 PM and 8 AM (as consistent with previous studies). Daily (24-hour) actigraphy sleep measures were calculated on nighttime and nap sleep intervals. Parameter estimates of minimum, acrophase, up-mesor, down-mesor, alpha, amplitude, mesor, and beta were derived from fitting actigraphy movement data to an ECM. A visual representation of the variables used in this study is presented in Fig. 1A and B.

**Variable selection and coding**

We used a total of 24 variables in our FA, which included both summary statistics from actigraphy and parameter estimates from ECM. Summary statistics of actigraphic sleep information were averaged across all valid days to represent the overall sleep characteristics of the participant across the study period. All variables included in this study were objective measures of participants’ sleep features and were commonly used in sleep research. Among these variables, 13 of them had highly skewed distributions. To facilitate the convergence of the model, we coded all variables into ordinal data with five categories (minimum from the ECM model only has three categories), using quintiles from the sample. This approach was consistent with the work by Wallace et al. Variables selected in the study are listed in Table 2 with descriptions.

**Mild cognitive impairment**

Participants were classified as having MCI or being cognitively unimpaired based on the Jak/Bondi algorithmic criteria of global neuropsychological test performance. This approach has been shown to produce stable MCI diagnoses and to identify individuals who will progress to dementia. The neuropsychological...
test battery included two tests in each of five cognitive domains: (1) Memory: free recall from the Free and Cued Selective Reminding Test, Benson Complex Figure (Delayed); (2) Executive Function: Trail Making Test Part B (limit time 300 second), Phonemic Verbal Fluency (Letters F and L for 1 minute each); (3) Attention: Trail Making Test Part A (limit 300 second), Number Span (forward and backward); (4) Language: Multilingual Naming Test (total score), Category Fluency (Animals, Vegetables: 1 minute each); (5) Visual-spatial: Benson Immediate Recall, Wechsler Adult Intelligence Scale III Block Design. A participant was classified as having MCI if they met one or more of the following criteria: (1) > 1 standard deviation (SD) below the age, gender, and education-adjusted normative means, on both measures within at least one cognitive domain; or (2) > 1 SD below the age, gender, and education adjusted normative mean, in each of three of the five cognitive domains measured; or (3) a score of 4 on the Lawton Brody scale. If a variable loaded multiple factors, we decided on the factor assignment based on the magnitude of the loading as well as theories and findings from previous studies.

Factor analysis methods

We randomly split the sample into two subsamples: the subsample with 100 participants was used for EFA and the rest of the data set (n = 189) was used for CFA. We kept more participants for CFA to ensure an adequate sample size for model fitting.

For EFA, we performed Bartlett’s test of sphericity ($P < .05$) to confirm that our sample had patterned relationships, and calculated the Kaiser-Meyer-Olkin measure to check sampling adequacy (cut-off is above 0.6). Given the data we used for EFA was coded as ordinal, polychoric correlations were used. We determined the number of factors by visually examining scree plots of eigenvalues, taking into consideration existing theories. We expected factors to be correlated; we used the oblimin rotation, an oblique rotation, and the default rotation of the `fa()` function in the `psych` package. The factoring method was minchi. A median imputation method was applied to handle missing data (ECM parameters for one participant). Consistent with a prior study, the factor loading cutoff was set at an absolute value > 0.4. If a variable loaded multiple factors, we decided on the factor assignment based on the magnitude of the loading as well as theories and findings from previous studies.

CFA was performed with the ordered data based on the factor structure identified by the EFA analysis. We performed separate CFAs for each factor to verify the single-factor structure based on the current sample size for CFA (n = 189). For factors with only two
variables loaded on them, the factor loadings of the two observed variables were constrained to be the same to make the factor model identifiable. Model fitting criteria included the comparative fit index, Tucker-Lewis index, the root mean square error of approximation (RMSEA), and standardized root mean square residual, commonly used in structural equation models. Residual variances were correlated when necessary based on model modification indices and theoretical reasons. Missing observations were handled using full information maximum likelihood to retain as much information as possible. CFA procedures were performed using the cfa() function in the lavaan package.\textsuperscript{29}

Illustration of the usage of the factor scores approach

Given the non-normal distributions of the factor scores, the distribution-assumption-free Mann-Whitney \textit{U} test was used to compare differences in factor scores for each of the factors for participants with and without MCI. The analysis was conducted in R.\textsuperscript{30} Effect sizes were evaluated using the Glass rank biserial correlation coefficient ($r_{gb}$), calculated using the \textit{wilcoxonRGC()} function in \texttt{rcompanion} library.\textsuperscript{31}

Associations of the six sleep health factors and global cognitive outcome (MoCA) were explored using multiple linear regression with MoCA score as the dependent variable and the factor scores of the six sleep health factors as independent variables. The model was controlled for demographic variables, including age, gender, years of education, and race. The procedure was performed using the \textit{lm()} function in R.\textsuperscript{30}

Results

Sample descriptive

Table 1 summarizes the demographic and clinical characteristics of the analytic sample. For the EFA sample, one participant did not have complete data. Four participants did not have complete data for CFA. The correlation of the variables was examined using both original continuous data (see Fig. 2A) and coded ordinal data (see Fig. 2B). The correlation matrix plots of the ordered data and the original continuous data showed very similar patterns and therefore coding the data into ordinals did not change the overall correlation structure.

EFA results

Bartlett’s test of sphericity was significant, with the overall measure of sampling adequacy of the EFA sample = 0.72. Scree plot of eigenvalues (Fig. 3) supported a six-factor structure given the steep decrease in the first six eigenvalues and the fact that the first six factors had eigenvalues larger than one. We, therefore, performed EFA assuming a six-factor structure. EFA results are summarized in Table 3. Labels for the factors were assigned based on the RU-SATED domains.

Factor 1: Duration (four variables)

This factor captures how long participants sleep or spend in bed on average during the day or at nighttime. Four variables, night rest interval(s), night total sleep time (TST), 24-hour TST, and 24-hour total rest interval(s) loaded on this factor. These four measures summarized the duration of sleep at night, duration of rest time (including wake after sleep onset [WASO]) during the night, duration of sleep during the day (including night sleep and daytime naps), and duration of rest time during the day. Sleep onset time had a loading above 0.4 (ie, $-0.44$) on the Duration factor, but its highest loading was on the second factor at 0.90. Therefore, we assigned the sleep onset time variable to the second factor (ie, Timing), based on its highest loading and the fact that theoretically, it is appropriate to have sleep onset time to cluster with other Timing related variables.

Table 1

<table>
<thead>
<tr>
<th>Variable name</th>
<th>Full sample (N = 289)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age, years, mean (SD)</td>
<td>77.4 (4.9)</td>
</tr>
<tr>
<td>Female, % (n)</td>
<td>68.5 (198)</td>
</tr>
<tr>
<td>Race, % (n)</td>
<td>White, non-Hispanic 45.0 (130) Black, non-Hispanic 41.5 (120) Hispanic 12.1 (35) Other 1.4 (4)</td>
</tr>
<tr>
<td>Education, years, mean (SD)</td>
<td>15.0 (5.6)</td>
</tr>
<tr>
<td>Marital status, % (n)</td>
<td>Married 32.2 (93) Separated 1.4 (4) Widowed 26.3 (76) Divorced 22.5 (65) Never married 17.7 (51)</td>
</tr>
<tr>
<td>Smoking status, % (n)</td>
<td>Current 3.5 (10) Former 35.3 (102) Never 41.2 (119) Missing 20.1 (58)</td>
</tr>
<tr>
<td>Depressive symptoms (The Geriatric Depression Scale), mean (SD)$^a$</td>
<td>2.3 (2.0)</td>
</tr>
<tr>
<td>Global cognition (MoCA; mean, SD)</td>
<td>23.7 (3.5)</td>
</tr>
<tr>
<td>Mild cognitive impairment (MCI), % (n)</td>
<td>Yes 30.8 (89) No 69.2 (200)</td>
</tr>
<tr>
<td>Hypoxemia, % (n)$^b$</td>
<td>28.0 (81)</td>
</tr>
<tr>
<td>Oxygen desaturation index, % (n)$^c$</td>
<td>13.2 (38)</td>
</tr>
</tbody>
</table>

MoCA, Montreal Cognitive Assessment; SD, standard deviation.

$^a$ Greater than five is suggestive of depressive symptoms.

$^b$ One participant did not provide data for global cognition.

$^c$ Total of 12 participants did not provide data for hypoxemia and oxygen desaturation index.

Factor 2: Timing (six variables)

The Timing factor captures when participants typically had their nighttime sleep. Among the six variables, three of them were from means of actiware summary statistics, including sleep onset time, wake-up time and midpoint. The remaining three variables were from the ECM model and also represented the timing of the curves. Specifically, the down-mesor corresponds to the time of switching from high to low activity, which is related to sleep onset time. Up-mesor represents the time of switching from low to high activity, which corresponds to wake-up time. Acrophase captures the time of maximum activity, or in other words, peaks of the curves.

Factor 3: Regularity (five variables)

The Regularity factor captures how much day-to-day variability participants had across a 16-day period in terms of sleep timing and duration, including midpoint, sleep onset time, wake-up time, 24-hour TST, and night TST. To facilitate interpretation, we reverse-coded the SD variables. Therefore, larger factor scores for the Regularity factor mean less variability and thus more regularity of the participants.

Factor 4: Alertness/sleepiness (four variables)

The Alertness/Sleepiness factor captures the wakefulness of participants during the daytime. The average number of naps per day and average minutes of napping per day represent the frequency and length of the naps of the participants during the daytime. The amplitude variable from ECM reflects the height of the peaks, where lower amplitude indicates less activity during daytime relative to nighttime. Daytime napping has been shown to reveal the accumulation of homeostatic sleep pressure (Polysomnographic delta...
power), or sleepiness. In turn, a nap generally increases subsequent alertness due to the dissipation of that homeostatic sleep drive. To facilitate interpretation, we reverse-coded number of naps and minutes of napping. We can expect participants with higher values of this factor to have less naps, shorter naps, and higher day-time activity levels. Beta from ECM also had the highest loading on this factor (−0.48). Beta represents how steep the curves are. Participants with low activity levels may have flatter curves and thus smaller beta estimates.

**Table 2**

<table>
<thead>
<tr>
<th>Variable name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Night rest interval(s)</td>
<td>Total number of minutes between nighttime sleep onset and sleep offset, including wake minutes.</td>
</tr>
<tr>
<td>Night total sleep time</td>
<td>Total number of minutes asleep between nighttime sleep onset and sleep offset.</td>
</tr>
<tr>
<td>24-h Total sleep time</td>
<td>Total number of minutes asleep between sleep onset and sleep offset for each sleep interval in a 24-h day.</td>
</tr>
<tr>
<td>24-h Rest interval(s)</td>
<td>Total number of minutes between sleep onset and sleep offset for each sleep interval in a 24-h day, including wake minutes during sleep intervals.</td>
</tr>
<tr>
<td>Midpoint</td>
<td>Sleep midpoint is determined as the midpoint timing between nighttime sleep onset and sleep offset (wake time). The sleep midpoint is a measure of circadian timing.</td>
</tr>
<tr>
<td>Wake-up time</td>
<td>Wake time is determined by the scored actigraphic nighttime sleep duration end time (sleep offset): the time of the first 30-s epoch of activity &gt; 10 counts that follow five consecutive epochs ≤ 10.</td>
</tr>
<tr>
<td>Sleep onset time</td>
<td>Sleep onset is determined by the scored actigraphic nighttime sleep duration start time: the time of the last 30-s epoch of activity &gt; 10 counts followed by five consecutive epochs ≤ 10, indicating sleep.</td>
</tr>
<tr>
<td>Up-mesor</td>
<td>Estimated time of the switch from low to high activity from the ECM.</td>
</tr>
<tr>
<td>Acrophase</td>
<td>Estimated time of maximum activity from the ECM.</td>
</tr>
<tr>
<td>Down-mesor</td>
<td>Time of switch from high to low activity from the ECM.</td>
</tr>
<tr>
<td>Standard deviation of midpoint</td>
<td>Sleep midpoint is determined as the midpoint timing between nighttime sleep onset and sleep offset (wake time). The standard deviation of this daily measure was calculated across valid actigraphy days per participant.</td>
</tr>
<tr>
<td>Standard deviation of sleep onset</td>
<td>Sleep onset is determined by the scored actigraphic nighttime sleep duration start time: the time of the last 30-s epoch of activity &gt; 10 counts followed by five consecutive epochs ≤ 10, indicating sleep. The standard deviation of this daily measure was calculated across valid actigraphy days per participant.</td>
</tr>
<tr>
<td>Standard deviation of wake time</td>
<td>Wake time is determined by the scored actigraphic nighttime sleep duration end time (sleep offset): the time of the first 30-s epoch of activity &gt; 10 counts that follow five consecutive epochs ≤ 10. The standard deviation of this daily measure was calculated across valid actigraphy days per participant.</td>
</tr>
<tr>
<td>Standard deviation of 24-h total sleep time</td>
<td>24-h total sleep time is the total number of minutes asleep between sleep onset and sleep offset for each sleep interval in a 24-h day. The standard deviation of this daily measure was calculated across valid actigraphy days per participant.</td>
</tr>
<tr>
<td>Standard deviation of night total sleep time</td>
<td>Night total sleep time is the total number of minutes asleep between nighttime sleep onset and sleep offset. The standard deviation of this daily measure was calculated across valid actigraphy days per participant.</td>
</tr>
<tr>
<td>Amplitude</td>
<td>Estimated amplitude from the ECM.</td>
</tr>
<tr>
<td>Number of naps per day</td>
<td>Number of naps is defined as the number of sleep intervals greater or equal to 20 min in duration within a 24-h day.</td>
</tr>
<tr>
<td>Minutes napping per day</td>
<td>Nap minutes are defined as the total minutes of napping per day. Naps were scored in sleep intervals equal to or longer than 20 min in duration.</td>
</tr>
<tr>
<td>Beta</td>
<td>Determines whether the function rises and falls more steeply than the cosine curve. Large values produce nearly square curves (abrupt switches from high to very low activity and from low to high activity).</td>
</tr>
<tr>
<td>Mesor</td>
<td>Estimated 24-h mean activity level, computed as Minimum + Amplitude/2.</td>
</tr>
<tr>
<td>Alpha</td>
<td>Width of peaks relative to troughs from ECM. Large values indicate the peaks are narrow (shorter period of daytime activity) and the troughs are wide (longer period of nighttime sleep); small values indicate the peaks are wide and the troughs are narrow.</td>
</tr>
<tr>
<td>Minimum</td>
<td>An estimated minimum level of activity from the ECM.</td>
</tr>
<tr>
<td>Sleep maintenance efficiency</td>
<td>Sleep maintenance efficiency is a measure of sleep quality. It is defined as the minutes of actual sleep between sleep onset and sleep offset divided by the nighttime sleep duration interval [%]. (Nighttime TST/Nighttime Sleep Duration Interval) * 100.</td>
</tr>
<tr>
<td>Wake after sleep onset (WASO)</td>
<td>Nighttime WASO is measured as the total minutes of wake between nighttime sleep onset and sleep offset. The wake threshold was set to medium sensitivity (40 activity counts for 1-min epochs) in Actiware software.</td>
</tr>
</tbody>
</table>

ECM, extended cosine model; TST, total sleep time.

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**Factor 6: Efficiency (two variables)**

The Efficiency factor captures the nighttime sleep quality of the participants. Two variables were loaded on this factor, including sleep maintenance efficiency (SMeff) and WASO. Sleep with high efficiency should have low values for WASO and high SMeff values.

**CFA results**

CFA was performed based on the structure identified by the EFA. We performed CFA on each individual factor using the subsample for CFA (n = 189), as appropriate for the current sample size and extent of variables. To facilitate model interpretation, WASO was reverse coded so that higher WASO values represent less WASO time. Number of naps and minutes of napping were reverse coded so that higher values represent less napping and more alertness. All SDs of variables were also reverse coded so that larger values represent less variability across days and hence more regularity. Beta was not included in the final CFA results because initial analysis showed the loading for the beta was low at 0.15 (je < 0.4 cutoff) and it was not significant (P = .16). Excluding beta from final CFA results was consistent with prior work.

Table 4 summarizes the CFA results. First of all, CFA models for the six factors met the model fitting indices criteria. Comparative fit index and Tucker-Lewis index for all six CFA models were high,
ran ging from 0.92 to 1. RMSEAs were < 0.05 for four out of the six CFA models. Even though CFA for the Alertness/Sleepiness factor had an RMSEA with a 90% confidence interval (CI) of (0.06, 0.21) and Timing factor had an RMSEA 90% CI of (0.18, 0.24), they met all other three models fitting criteria and therefore we did not consider it as a major sign of model misfit. Standardized root mean square residuals for all models were < 0.08, ranging from 0.008 to 0.05.

Factor loadings for all factors based on the factor structure were all significant with a magnitude > 0.40, confirming the factor structure we previously identified. The magnitude of the factor loadings offers information on the importance of each measure in

<table>
<thead>
<tr>
<th>Factor</th>
<th>Night rest interval(s)</th>
<th>Night total sleep time</th>
<th>24-h Total sleep time</th>
<th>24-h Total rest interval(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>F1: Duration</td>
<td>0.94</td>
<td>0.01</td>
<td>-0.17</td>
<td>0.04</td>
</tr>
<tr>
<td>F2: Timing</td>
<td>0.99</td>
<td>0.04</td>
<td>0.17</td>
<td>0.01</td>
</tr>
<tr>
<td>F3: Regularity</td>
<td>0.97</td>
<td>0.02</td>
<td>0.25</td>
<td>-0.03</td>
</tr>
<tr>
<td>F4: Alertness/Sleepiness</td>
<td>0.85</td>
<td>0.04</td>
<td>0.29</td>
<td>-0.02</td>
</tr>
<tr>
<td>F5: Rhymicity</td>
<td>0.04</td>
<td>0.03</td>
<td>0.05</td>
<td>-0.04</td>
</tr>
<tr>
<td>F6: Efficiency</td>
<td>0.10</td>
<td>0.03</td>
<td>0.83</td>
<td>-0.04</td>
</tr>
</tbody>
</table>

Factor 1: Duration
Night rest interval(s) 0.94 0.01 -0.17 0.04 0.17 0.09
Night total sleep time 0.99 0.04 0.17 0.01 0.09
24-h Total sleep time 0.97 0.02 0.25 -0.03 0.10
24-h Total rest interval(s) 0.85 0.04 0.29 -0.02 -0.23

Factor 2: Timing
Midpoint -0.04 0.98 -0.09 -0.01 -0.05 0.04
Wake-up time 0.36 0.87 -0.04 0.11 -0.07 0.06
Sleep onset time -0.44 0.90 -0.04 -0.03 -0.07 0.06
Up-Mesor 0.22 0.87 -0.03 0.30 0.32 -0.01
Acrophase 0.07 0.85 0.06 -0.02 -0.22 0.09
Down-Mesor -0.10 0.57 0.16 0.05 -0.66 -0.02

Factor 3: Regularity (SD = standard deviation)
SD Midpoint (bed to wake-up) 0.10 0.03 0.83 -0.04 0.05 0.05
SD Sleep onset time 0.01 0.01 0.86 0.01 -0.12 0.06
SD Wake-up time 0.13 -0.08 0.80 -0.04 0.09 0.03
SD 24-h Total sleep time 0.00 -0.04 0.87 -0.21 -0.04 0.07
SD Night total sleep time -0.07 -0.03 0.90 0.02 -0.02 0.02

Factor 4: Alertness/Sleepiness
Amplitude 0.02 0.02 0.86 0.02 0.08 -0.24
Number of naps per day -0.15 0.02 0.20 -0.81 0.02 0.02
Minutes napping per day -0.01 0.04 0.28 -0.83 0.10 0.05
Beta 0.25 -0.01 -0.44 -0.48 -0.26 -0.15

Factor 5: Rhymicity
Mesor -0.35 0.05 0.00 -0.27 0.72 -0.11
Alpha 0.38 0.08 -0.07 -0.08 0.74 -0.06
Minimum -0.13 0.06 0.11 0.37 0.74 -0.20

Factor 6: Efficiency
Sleep maintenance efficiency 0.18 0.01 0.02 -0.07 -0.04 0.98
Wake after sleep onset -0.19 0.01 0.04 0.04 0.03 0.94
constructing the factor. For the Duration factor, 24-hour TST (1.42) and 24-hour total rest interval(s) (1.27) were the two most important factors. For the Timing factor, the three most important factors were midpoint (1.41), sleep onset time (1.27), and acrophase (1.31). SD of 24-hour TST (1.27) and night TST (1.35) contributed the most to the Regularity factor. For the Alertness/Sleepiness factor, the two napping-related factors contributed similarly (1.39 and 1.41). Mesor (0.71) contributed the most to the Rhythmicity factor. The factor loadings of the two variables for the Efficiency factor were constrained to be the same to make the CFA model identifiable.

Results for examining the association between factor scores and global cognitive function

Multiple linear regression was performed to examine the association between global cognitive performance (MoCA) and the factor scores of the six sleep health factors. Results are summarized in Fig. 4. After controlling for demographic variables, age, gender, years of education, and race, the model is significant with $F(10,267) = 8.26$, $P < .01$, and the model explained $22\%$ of the variability in MoCA (Adjusted $R^2 = 0.22$). Among the six sleep health factors, Efficiency was found to be significantly associated with MoCA performance, with participants who had greater sleep efficiency performing better on MoCA ($\beta = 0.63 [0.19, 1.08]$).

Mann-Whitney $U$ tests were performed on each of the sleep factors to examine whether participants with or without MCI differ in the factor scores of each of the sleep dimensions. Results showed that participants without MCI ($N = 200$) tended to have more regularity in their sleep (median = 0.07, interquartile range (IQR) = $[-0.75, 0.95]$) compared to their MCI counterparts ($N = 89$, median = −0.18, IQR = $[-0.90, 0.64]$), but the difference was not statistically significant ($W = 10,126$, $P = .06$, $rg = 0.14$). In addition, a difference in sleep efficiency was also noted, but not statistically significant ($W = 9964.5$, $P = 1$, $rg = 0.12$), with non-MCI participants having more efficient sleep than participants with MCI (non-MCI group median = 0, IQR = $[-0.70, 1.05]$; MCI group median = 0, IQR = $[-1.05, 0.70]$). Future research with larger samples was required to further examine this effect. For the remaining four sleep dimensions (ie, Duration, Timing, Alertness/Sleepiness, Rhythmicity), no statistically significant differences were noted between MCI and non-MCI groups (Fig. 5).

Discussion

In this study, we used EFA to identify a six-dimension factor structure comprising the sleep health of older adults from 2 weeks of objectively collected actigraphy data and then validated the structure with CFA. The six factors were: Timing, Efficiency, Duration, Alertness/Sleepiness, Regularity, and Rhythmicity. Five of the six domains identified (all except Rhythmicity) were highly consistent with domains proposed in the RU-SATED model, excluding the Satisfaction domain because of its subjective nature. Five of these domains corroborate prior work on empirically derived sleep domains for older adults in particular. The sixth factor, Rhythmicity, was not found in prior work and was identified in this analysis potentially due to the longer duration of actigraphy recording. The identified six-factor structure based solely upon objective (device-derived) data contributes an empirical step forward for the theoretical framework of multi-dimensional sleep health.

We named our five factors based both on prior work with which our factor contents were consistent and based on their contents. The Duration factor represents durations of rest intervals, as well as TST (ie, rest interval − WASO), both for the 24-hour sleep period and night sleep period. The Timing factor captures major time points when sleep starts (ie, sleep onset time and down-mesor), sleep ends (ie, wake-up time and up-mesor), sleep midpoint, and the highest point of day-time activity level (ie, acrophase). The Regularity factor describes day-to-day fluctuations of both timings of sleep (eg, marked by the midpoint, sleep onset time, and wake-up time) and duration of sleep (ie, 24-hour TST and night TST). Napping was largely captured within the Alertness/Sleepiness factor, as it may reflect the behavioral manifestation of sleep pressure. The Alertness/Sleepiness factor is also indicated by amplitude, which reflects peak intensity of activity. The Efficiency factor is characterized by high levels of SMeff and low values of WASO.

The novel sixth factor, Rhythmicity, included mesor, alpha, and minimum from ECM. These were all derived using an ECM, which describes day-to-day fluctuations of both levels of SMeff and low values of WASH.

The novel sixth factor, Rhythmicity, included mesor, alpha, and minimum from ECM. These were all derived using an ECM, which describes day-to-day fluctuations of both levels of SMeff and low values of WASH.
Our study identifies six multidimensional sleep health facets in a population of older adults using a FA of objective sleep measures. These findings extend the literature by introducing a Rhythmicity dimension, which is especially important for health in older adults. These sleep health factors can be considered predictors of health outcomes, and targets for sleep interventions in older adults.
Disclosures

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