

Association of Longitudinal Sleep and Next-day Indoor Mobility Measured via Passive Sensors among Community-dwelling Older Adults

Yang Gao^{1,2}, Mahnoosh Kholghi², Irena Koprinska¹, and Qing Zhang²

Abstract—Previous studies have shown there is a relationship between sleep and mobility in older adults by collecting and analysing self-reported data from surveys and questionnaires, or by using objective measures from polysomnography or actigraphy. However, these methods have limitations for long-term monitoring, especially for community-dwelling adults. In this paper, we investigate the association between sleep and indoor mobility using longitudinal data collected over a period of about 12 months for older adults (65 years or older) living at home in Australia. The data was collected objectively and continuously using non-invasive and passive sensors. First, we explored whether sleep and indoor mobility are different across gender and age groups (70s, 80s, and 90s). Second, we investigate the association of sleep and next-day indoor mobility through a stepwise multivariate regression. We found that males and females have significant differences in mobility, time in bed, total time in sleep, number and duration of awakenings and sleep efficiency. Additionally, mobility and all sleep measures significantly vary across the three age groups, except for sleep onset latency between 80s and 90s. Our findings show that sleep efficiency and total sleep time are the key sleep measures affecting next-day mobility, while sleep onset latency has the least effect.

Clinical relevance - Our study contributes to a better understanding of the sleep patterns of older adults and how they affect their physical functioning.

I. INTRODUCTION

Poor sleep and reduced physical activity, which are commonly reported by older adults, may lead to a significant decline in health and well-being over time. It has long been recognized that exercise can improve sleep quality [1]. On the other hand, poor sleep and sleep disturbances can limit the physical functioning of older adults [3]. In this paper we study the relationship between sleep and the next-day mobility of older adults (aged 65 and older) living at home in Australia, where motion and sleep are measured objectively using non-obstructive sensors over a long period of time.

Sleep and physical activity are typically assessed using self-reported measures. For example, Valenza et al. (2013) [5] employed two questionnaires (Pittsburgh

Sleep Quality Index and the Functional Status Questionnaire) to study the correlation between sleep and mobility. However, self-reported answers from surveys may be biased by personal perceptions and poorly correlated with objective measures [4]. Recent studies used a mixture of subjective and objective measures [6, 16]. The objective measures are typically based on: (1) lab-restricted measures of sleep (using polysomnography) and activity (direct measurements of walking steps or speed), or (2) sleep-wake cycles measured via actigraph, worn on the dominant wrist for at least 7 days. Objective measures of sleep and physical activity assessed in lab-based environments are not only invasive and expensive, but also do not reflect the participant's natural living environment. Actigraphy has also many limitations for longitudinal monitoring, including the limited battery life and the requirement to wear it continuously, which may not be always convenient or the participants may forget to do it.

There is a need to better understand the relationship between sleep and physical activity for older adults monitored in their natural living environment over a long period of time, without any disruption to their daily routine. This includes understanding the sleep and activity differences across age and gender, to inform better support and in-home interventions. With the recent advances in smart home technologies, home-based sensor networks were proposed to support independent-living through continuous monitoring of health and wellbeing [7-10]. They can facilitate longitudinal monitoring of sleep and daily living activities in the home environment, as non-intrusive and passive sensors best align with the natural lifestyle of older adults. Another advantage of in-home sensors is their ability to capture spatio-temporal features of the events, which allows to investigate not only the immediate, but also the long-term association between sleep and mobility.

In this paper, we investigated the the association of sleep and indoor mobility captured over a year from Australian community-dwelling older adults (aged 65 and older). The data was collected objectively and continuously through non-invasive and passive sleep and motion sensors. We considered six objective sleep

¹The University of Sydney, Sydney, NSW, Australia

²The Australian e-Health Research Centre, Health and Biosecurity, CSIRO, Brisbane, QLD, Australia

measures and a measure of indoor mobility to explore: 1) the differences between sleep and mobility across gender and age groups (70s, 80s, and 90s), and 2) how sleep affects next-day mobility.

II. METHOD

A. Study design

This study is part of the Dementia and Aged Care Services (DACS) project which involved 200 community-dwelling residents aged 65 and over in a randomised control trial. All participants lived in their homes in Brisbane, Australia, and received low-level age care service (visits by a carer to help with daily activities 1-2 times a week). Half of the participants were equipped with the Smarter Safer Homes package [13], which included passive motion and sleep sensors.

To ensure high data quality, we only included data from participants who lived alone. To avoid the impact of cognitive problems on the measurements, only cognitively healthy participants (as confirmed by the Abbreviated Mental Test [14]) were included in our analysis. This resulted in 36 participants for our study - 13 males and 23 females - with an average age of 83.5 ± 7 years. As the participants could withdraw from the study during the monitored period, the length of the recorded data ranged from 15 to 378 days. In total, 7847 valid days of sensor measurements were recorded from 36 participants.

B. Data collection

The sensor data used in this study is continuous motion and sleep data. In particular, we computed indoor mobility, since we only deployed non-wearable sensors inside their homes. Daily steps, as a measure of mobility, is key to the assessment of physical functioning [11]. We followed the same approach proposed in [12] to quantify indoor mobility through travelled distance derived from passive infrared (PIR) sensors and topological indoor maps.

The mobility data was collected using off-the-shelf PIR motion sensors with a 5-metre motion detection range and 120-degree field of view. The motion sensors were installed in the participant's home, in the corners of the rooms near the ceilings, to detect all movements including entering and exiting the room. Due to the small room sizes, only one sensor per room was deployed, ensuring that the field of views of adjacent rooms do not overlap and thus avoiding simultaneous triggers by multiple sensors.

Table I shows an excerpt of the PIR motion data for one participant. The motion sensor has a cooling-off period of 4 minutes. Once the sensor is triggered by the first movement, a value of '1' is transmitted to a

centralized database and the 4-minute period starts. If any further movement is detected within the cooling-off period, no value will be sent to the database, but the sensor re-starts the 4-minute period. In case of no trigger within the cooling-off period, a value of '0' is sent at the end of the period. The use of cooling-off period reduces the values sent back and thus maximizes the sensor's battery life. Table II is a pairwise sensor-to-sensor distance map in number of steps, measured by our team.

TABLE I: An excerpt from PIR motion sensor data of one participant.

Motion sensor ID	Sensor location	Local timestamp	Value
7184	bedroom	22/10/2019 18:51	1
7209	bathroom	22/10/2019 18:57	1
7209	bathroom	22/10/2019 19:01	0
7194	living room	22/10/2019 19:09	1
7189	kitchen	22/10/2019 19:09	1
7194	living room	22/10/2019 19:13	0
7189	kitchen	22/10/2019 19:15	1
7189	kitchen	22/10/2019 19:19	0

TABLE II: Topological room distance map (in steps) of PIR sensors deployed in different rooms.

To \ From	Bedroom	Bathroom	Study	Kitchen	Living room
Bedroom	-	4	5	16	12
Bathroom	4	-	5	14	14
Study	5	5	-	12	10
Kitchen	16	14	12	-	7
Living room	12	14	10	7	-

The sleep data was collected using an unobtrusive mattress-based EMFIT sensor [2]. This is a ballistocardiography-based sensor which measures mechanical chest wall movements from heartbeat and respiration, from which sleep measures are then inferred. A sleep episode is recorded from the time the person goes to bed until they leave the bed. If the individual leaves the bed for more than 10 minutes and then returns, another sleep episode will be recorded. Hence, multiple sleep episodes may be recorded during the night.

C. Sensor data processing

Mobility is represented by the daily travelled distance in steps within the time frame from 6am to 11:59pm. This is achieved by firstly removing repetitive PIR sensor logs where the recordings did not indicate inter-sensor transitions, and then summing the inter-sensor steps using the indoor distance maps.

Sleep is measured at night, by extracting sleep measures from the sleep episodes recorded from 7pm on the

current day until 6am on the next day. A mobility measure was then extracted from 6am on the next day. This is referred to as "next-day mobility" in our analysis. The sleep measures used in our analysis include: Total Sleep Time (TST), Sleep Onset Latency (SOL), Wake After Sleep Onset (WASO), Total duration In Bed (TIB), number of awakenings (Awake), and Sleep Efficiency (SE, which is TST divided by TIB). Days with mobility equal to 0, any wrong status for any motion sensor, or no nocturnal sleep were all excluded from our analysis.

D. Data Analysis

To investigate if there are significant differences in sleep and mobility between gender and age groups, we used the Mann-Whitney U test between the 13 males and 23 females, and the Kruskal-Wallis test with Dunn's post-hoc test for comparison among the three age groups (12 people in their 70s, 15 in their 80s, and 9 in their 90s). These tests were selected after using the Shapiro-Wilk test to assess whether the sleep and mobility measures were normally distributed.

To explore the effect of sleep on next-day mobility, we used linear regression analysis. The independent variables are the six sleep measures (TST, SOL, WASO, TIB, SE, and Awake) and the dependent variable is the next-day mobility. First, an ordinary least squares multiple regression model was built for data from each participant, and then a stepwise analysis was applied to select the optimal variables that have significant impact on next-day mobility. This analysis adds or deletes variables from the linear model in a forward and backward process to determine an optimal model. The criteria of the stepwise model were set to obtain the smallest SSE (sum of squared residuals) error, which measures how well the model fits the data, while keeping the t-statistic of the variables significant ($<.05$).

We further analysed the selected optimal variables from the 36 individual models across gender and age groups to investigate which are the most frequently selected sleep parameters.

III. RESULTS

A. Differences in sleep and mobility across age and gender

Table III shows the mean values and standard deviation for the objective measurements of mobility and sleep across gender and age groups, and Table IV presents the statistical test results.

While the sleep onset latency (SOL) was similar across males and females, female had higher mobility than males, longer sleep (TST) and time in bed (TIB), longer wake after sleep onset (WASO), higher number of awakes (Awake) and slightly higher sleep efficacy

(SE). The results showed that males and females had significant ($p <.05$) differences in mobility and sleep patterns, except for SOL.

Comparing the three age groups (70s, 80s, and 90s), we observed that there are variations in sleep and mobility. While the number of awakenings (Awake) and their duration (WASO) increases with age, there is an increase-decrease trend in TST, TIB, and SE, decrease-increase in mobility, and only slight differences in SOL. Table IV (b) shows that all differences across the age groups were statistically significant, except for SOL between 80s and 90s ($p = 0.002 > 0.05/3$), as indicated by Dunn's post-hoc test.

Variables	Male (n = 13)	Female (n = 23)
Mobility (steps)	580.87 ± 334.99	652.14 ± 361.86
TST (hours)	6.82 ± 2.37	7.01 ± 1.92
SOL (minutes)	25.03 ± 12.75	24.56 ± 12.84
WASO (minutes)	78.70 ± 32.95	83.00 ± 40.71
TIB (hours)	7.94 ± 2.49	8.14 ± 2.01
Awake (number)	1.81 ± 1.53	1.97 ± 1.57
SE (TST/TIB)	0.85 ± 0.07	0.86 ± 0.07

(a)

Variables	70s n = 12 (5 males, 7 females)	80s n = 15 (7 males, 8 females)	90s n = 9 (1 male, 8 females)
Mobility (steps)	624.13 ± 336.99	575.83 ± 361.08	702.60 ± 343.89
TST (hours)	6.17 ± 2.21	7.69 ± 1.92	6.64 ± 1.87
SOL (minutes)	24.00 ± 11.61	24.90 ± 13.36	25.60 ± 13.34
WASO (minutes)	76.06 ± 38.12	82.54 ± 40.62	86.08 ± 29.94
TIB (hours)	7.24 ± 2.36	8.80 ± 2.01	7.87 ± 1.93
Awake (number)	1.58 ± 1.33	1.93 ± 1.72	2.31 ± 1.42
SE (TST/TIB)	0.84 ± 0.08	0.87 ± 0.06	0.84 ± 0.07

(b)

TABLE III: Descriptive statistics (mean and standard deviation): (a) by gender, (b) by age group

B. Association between sleep and next-day mobility

A stepwise multivariate linear regression model using the six sleep parameters as independent variables and the next-day mobility as a dependent variable was built per participant, resulted in total of 36 models. Table V shows some examples of the models' output with their coefficients and adjusted R^2 , where a significant association between sleep and mobility was observed ($p <.05$).

An inspection of the adjusted R^2 of the 36 individual models (mean value and standard deviation: 0.871 ± 0.079) showed that the value was greater than 80% for 34 of them, while for the other 2, it was between 0.6 and 0.8. This suggests 80% of the variance in the next-day mobility can be explained by the objectively measured sleep for the majority of participants. In addition, the high value of adjusted R^2 indicates that the selected sleep variables were useful and added value to the model.

An in-depth analysis of the effect of the sleep measures for each group and overall is shown in Table VI.

Variables	Mann-Whitney U statistic	p value
Mobility	6678801	< .01
TST	6913441	< .01
SOL	7375678	.075
WASO	7312716	.019
TIB	6896971	< .01
Awake	7074973	< .01
SE	7028830	< .01

(a)

Variables	Kruskal-Wallis H statistic	p value	Variables	70 vs 80	70 vs 90	80 vs 90
Mobility	222.99	< .01	Mobility	< .01	< .01	< .01
TST	781.48	< .01	TST	< .01	< .01	< .01
SOL	25.66	< .01	SOL	.015	< .01	.002
WASO	196.90	< .01	WASO	< .01	< .01	< .01
TIB	701.95	< .01	TIB	< .01	< .01	< .01
Awake	303.54	< .01	Awake	< .01	< .01	< .01
SE	483.30	< .01	SE	< .01	< .01	< .01

(b)

TABLE IV: Comparison of sleep and mobility: (a) by gender - Mann-Whitney U test, (b) by age group - Kruskal-Wallis H test and p-values of post-hoc Dunn's test.

We found that SE was the most important variable - it had a significant effect on next-day mobility in 35 out of 36 regression models. WASO appears as a key measure in 17 out of 36 models; however, its coefficients are much smaller (ranging from 0.4 to 3.5) compared to the other variables, which suggests that it only has a slight effect on the next-day mobility. TST was the next most important variable, appearing in 13 out of 36 models. SOL had the least effect on next-day mobility with no significant effect on next-day mobility for the 80s age group.

TABLE V: Examples of the stepwise multivariate models.

Age	Gender	Valid days	Adjusted R^2	Coefficients (p < .05)					
				TST	SOL	WASO	TIB	Awake	SE
79	male	323	0.82	-23.26		1.67		-31.14	698.78
79	female	157	0.89			1.20			646.55
89	male	171	0.85						542.06
83	female	87	0.94			0.923			163.07
90	male	298	0.81		-3.54				954.83
91	female	179	0.93	-117.12		0.98	66.78		802.42

IV. DISCUSSION

The purpose of our study was to investigate the association of sleep and mobility in older adults (age 65 and over), where the mobility and sleep were objectively and continuously measured with non-obstructive sensors over a long period of time (up to 378 days). In particular, we investigated differences across gender (males and females) and age groups (70s, 80s and 90s). We also studied the effect of six different sleep measures on

TABLE VI: Number of occurrences of the sleep parameters with significant effect on next-day mobility, derived from the 36 multivariate models when grouped per gender and age.

Total number of occurrences	TST	SOL	WASO	TIB	Awake	SE	
	13	4	17	7	5	35	
Age-wise occurrence	70s	5	3	8	2	1	12
	80s	5	0	6	2	3	14
	90s	3	1	3	3	1	9
Gender-wise occurrence	Male	6	2	5	2	3	13
	Female	7	2	12	5	2	22

next-day mobility using stepwise multivariate regression models.

We found that sleep and mobility varied significantly across gender. Women had statistically significantly higher mobility and higher values of all sleep parameters, except for sleep onset latency (SOL). Sivertsen et al. [17] found that SOL was statistically significantly longer in women than men. However, their study included younger participants - aged 40 years and older, so the results are not fully comparable.

There were also significant differences in mobility and sleep between the three age groups, except for SOL between 80s and 90s. As people get older, we observed an increase in both the number and duration of awakenings. There was a significant increase in mobility between 80s and 90s. On the other hand, there was an increase-decrease trend in TST, TIB and SE. The decrease in sleep efficiency (SE) in the 90s is due to the decreased sleep (TST) and bed duration (TIB).

Sullivan Bisson et al. [15] showed that walking is related to better sleep quality rather than longer sleep duration; however, it was unclear if mobility was more closely related to SE or TST. A similar study, that employed actigraphy-derived measures of walking steps and sleep, showed no significant correlation between daily walking steps and sleep duration [16].

The results of the 36 stepwise regression models showed that the most important sleep measure associated with the next-day mobility was the sleep efficiency. There was only one exception - the regression model of a 88-old female based on data from 160 days, where TIB had the biggest effect on mobility. Our analysis also showed that SE had a direct relationship with mobility regardless of age and gender. Therefore, the increase in sleep efficiency was associated with a greater next-day mobility for this cohort of participants.

This study has several limitations: (1) the sample size is relatively small, (2) the accuracy of the measurements of the sleep sensor may need further investigation, and (3) within-room steps were not included, as the PIR sensors and room topological maps cannot gauge activities in the same room. Nonetheless, this is the

first study to continuously and objectively monitor older adults' mobility and sleep over a long period of time while not interrupting their daily life routines. The results from our study can be used to promote in-home interventions to improve the health and well-being of community-dwelling older adults.

V. CONCLUSION

This study showed that there is a significant difference in sleep and mobility of older adults across gender and age groups. Our finding also suggest that sleep efficiency and total sleep time are the key factors affecting next-day mobility of older adults regardless of age and gender.

In future work we plan to investigate the effect of mobility on the next night sleep and how different activity levels in different times of the day can influence sleep. We also aim to use machine learning techniques to predict sleep as a function of mobility.

ACKNOWLEDGMENT

This study is part of the Dementia and Aged Care Services (DACS) project, which was funded by the Dementia and Aged Care Services Fund, the Department of Health Australia, grant number 4-4ZYS55Q. This project was granted approval by the CSIRO Health and Medical Human Research Ethics Committee (CHMHREC) - Proposal HREC 4/2018.

REFERENCES

- [1] M. Banno, Y. Harada, M. Taniguchi, R. Tobita, H. Tsujimoto, Y. Tsujimoto, Y. Kataoka, and A. Noda, "Exercise can improve sleep quality: A systematic review and meta-analysis," in *PeerJ*, vol. 6, no. 7, pp. e5172-e5172, 2018.
- [2] D. Huysmans, P. Borzee, D. Testelmans, B. Buyse, T. Willems, S. V. Huffel, and C. Varon, "Evaluation of a commercial ballistocardiography sensor for sleep apnea screening and sleep monitoring," in *Sensors*, vol. 19, no. 9, pp.2133, 2019.
- [3] K. P. Loh, C. Pandya, J. Zittel, S. Kadambi, M. Flannery, N. Reizine, A. Magnuson, G. Braganza, K. Mustian, W. Dale, P. Duberstein, and S. Mohile, "Associations of sleep disturbance with physical function and cognition in older adults with cancer," in *Supportive Care in Cancer*, vol. 25, no. 10, pp. 3161-3169, 2017.
- [4] J. Hughes, Y. Song, C. Fung, J. Dzierzewski, M. Mitchell, S. Jouldjian, K. Josephson, and C. Alessi, "Measuring sleep in vulnerable older adults: a comparison of subjective and objective sleep measures," in *Clinical Gerontologist*, vol. 41, no. 2, pp. 145-157, 2018.
- [5] M. C. Valenza, I. Cabrera-Martos, L. Martín-Martín, V. M. Pérez-Garzón, C. Velarde, and G. Valenza-Demet, "Nursing homes: impact of sleep disturbances on functionality," in *Archives of Gerontology and Geriatrics*, vol. 56, no. 3, pp. 432-436, 2013.
- [6] Y. Song, J. M. Dzierzewski, C. H. Fung, J. C. Rodriguez, S. Jouldjian, M. N. Mitchell, K. R. Josephson, C. A. Alessi, and J. L. Martin, "Association between sleep and physical function in older veterans in an adult day healthcare program," in *Journal of the American Geriatrics Society*, vol. 63, no. 8, pp. 1622-1627, 2015.
- [7] K. Obayashi, N. Kodate and S. Masuyama, "Can connected technologies improve sleep quality and safety of older adults and care-givers? An evaluation study of sleep monitors and communicative robots at a residential care home in Japan", in *Technology in Society*, vol. 62, p. 101318, 2020.
- [8] I. Sadek and M. Mohktari, "Non intrusive remote monitoring of sleep in home-based situation", in *Journal of Medical Systems*, vol. 42, no. 4, 2018.
- [9] P. Dawadi, D. Cook and M. Schmitter-Edgecombe, "Smart home-based longitudinal functional assessment", in *Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct Publication*, 2014.
- [10] P. Dawadi, D. Cook and M. Schmitter-Edgecombe, "Automated Cognitive Health Assessment From Smart Home-Based Behavior Data", in *IEEE Journal of Biomedical and Health Informatics*, vol. 20, no. 4, pp. 1188-1194, 2016.
- [11] W. H. Organization, *Global age-friendly cities: a guide*. (2007). Accessed: Jul. 16, 2021. [Online]. Available: <https://apps.who.int/iris/handle/10665/43755>
- [12] Q. Zhang, M. Karunanithi, D. Bradford, and Y. van Kasteren. "Activity of daily living assessment through wireless sensor data," in *2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, pp. 1752-1755.
- [13] Y. van Kasteren, D. Bradford, Q. Zhang, M. Karunanithi and H. Ding, "Understanding smart home sensor data for ageing in place through everyday household routines: a mixed method case study", in *JMIR mHealth and uHealth*, vol. 5, no. 6, p. e52, 2017.
- [14] H. Hodkinson, "Evaluation of a mental test score for assessment of mental impairment in the elderly", in *Age and Ageing*, vol. 1, no. 4, pp. 233-238, 1972.
- [15] A. N. Sullivan Bisson, S. A. Robinson, and M. E. Lachman, "Walk to a better night of sleep: testing the relationship between physical activity and sleep," in *Sleep Health*, vol. 5, no. 5, pp. 487-494, 2019.
- [16] N. Kimura, Y. Aso, K. Yabuuchi and E. Matsubara, "Association between objectively measured walking steps and sleep in community-dwelling older adults: A prospective cohort study", in *PLOS ONE*, vol. 15, no. 12, p. e0243910, 2020.
- [17] B. Sivertsen, S. Pallesen, O. Friborg, K. Nilsen, Bakke, J. Goll, and L. Hopstock, "Sleep patterns and insomnia in a large population-based study of middle-aged and older adults: the Tromsø study 2015-2016", in *Journal of Sleep Research*, vol. 30, no. 1, 2020.