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Is Complexity of Daily Activity Associated with Physical Function and Life-Space Mobility among Older Adults?

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ABSTRACT

RANTALAINEN, T., K. KOIVUNEN, E. PORTEGIJS, T. RANTANEN, L. PALMBERG, L. KARAVIRTA, and S. CHASTIN. Is Complexity of Daily Activity Associated with Physical Function and Life-Space Mobility among Older Adults? *Med. Sci. Sports Exerc.*, Vol. 54, No. 7, pp. 1210–1217, 2022. **Purpose:** Information about mobility and physical function may be encoded in the complexity of daily activity pattern. Therefore, daily activity pattern complexity metrics could provide novel insight into the relationship between daily activity behavior and health. The purpose of the present study was to examine the association between the complexity of daily activity behavior and the mobility and physical function among community-dwelling older adults 75, 80, and 85 yr of age. **Methods:** A total of 309 participants wore accelerometers concurrently on the thigh and the trunk for at least three consecutive days. Five activity states (lying, sitting, standing, walking, or activity other than walking) were defined in three different temporal grains (5 s, 1 min, and 5 min), and Lempel–Ziv complexity was evaluated. We assessed complexity of daily activity behavior using the life-space mobility and physical function with distance in preferred pace 6-min walk and the Short Physical Performance Battery. **Results:** Weak positive associations were observed between the complexity of daily activity and the mobility and physical function at the finest temporal grains in both sexes (Spearman rho = 0.19 to 0.27, $P < 0.05$). No significant associations were observed in the coarsest temporal grain in either sex. **Conclusions:** Lempel–Ziv estimates of daily activity complexity with a fine temporal grain seem to be associated with community-dwelling older adults' physical function. The coarsest 5-min temporal grain may have smoothed out physiologically meaningful short activity bouts. Because complexity encodes information related to timing, intensity, and patterning of behavior, complexity of activity could be an informative indicator of future physical function and mobility. **Key Words:** WEARABLE, ACTIGRAPHY, HABITUAL, AMBULATORY

Mobility (ambulatory and transportation) (1,2) and physical activity (3) decline with age. It is thought that this age-associated decline in mobility (2) is

at least partially driven by the age-associated decline in physical function (4–6). Mobility and physical activity are rather inextricably linked because getting from point A to B requires at least some ambulation. This link between mobility and physical activity has been leveraged in gerontological research by designing research tools to quantify mobility. One such tool probes the extent of the geographical area that a particular individual covers in going through their daily activities and the frequency of travel (life-space assessment) (7). Life-space assessment has subsequently been shown to be associated with physical activity in that those with larger life space also had more physical activity (8), and this association has been further corroborated by prospective findings, where a decreasing physical activity was associated with a diminishing life space among community-dwelling older adults (9). Moreover, mobility is strongly linked with quality of life and has strong prognostic value for disability and survival among older adults (2).

In addition to higher physical function, a larger life-space mobility may also mean a greater richness and freedom of movement, which might be reflected in the temporal pattern

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of different activities (10). It has been suggested that the structures of movement patterns include information that may not be captured with traditional measures of activity (11). More complex patterns in physiological or behavioral time series may characterize system's integrity and better ability to adapt flexibly to internal and external perturbations (12). At the functional level, this may be observed, for example, as capability for altering motor behavior to adapt to different task demands (13) and, consequently, larger life space.

However, mobility patterns are challenging to quantify because of the multidimensional nature of daily activity behavior. Mobility patterning may be influenced by, for example, the activity type, intensity, duration, and frequency (14). Recognizing activities based on body-worn sensors is not a trivial task, and age-related decrease in vigor of movements (15,16) can further increase the difficulty of activity classification (15). Furthermore, the number and placement of wearable sensors affects the precision of recognizing activity classes (17). These challenges have been tackled with concurrent trunk and thigh-worn accelerometers, which enables robust classification of postures throughout the day (13,18), while still retaining a reasonable participant burden (13,17). Posture assessments may be particularly informative in daily activity behavior containing a large volume of stationary behavior where the distinction between sitting and standing may be of interest (19).

Having captured the daily activity behavior, the pattern needs to be quantified and described numerically from the recorded activity states (e.g., lying, sitting, standing, and ambulation) to enable statistical analyses (10). A new approach to describe patterns of daily activity behavior assessed with concurrently worn devices is to use complexity metrics (such as Lempel–Ziv complexity [20]), which could add value to activity volume quantifications. Complexity metrics enable encoding information regarding activity patterning without requiring a known underlying structure of the patterning. Indeed, Paraschiv-Ionescu and colleagues (10) have explored the use of complexity metrics as a way to quantify daily activity behavior without considering the volume of physical activity, and they found that people with chronic pain and fear of falling can be discriminated from nonaffected referents based on daily activity complexity assessed with prolonged accelerometer samples (14). Moreover, the same group has reported that changes in balance and physical function were associated with daily activity complexity after a 4-wk exercise intervention in 60–70 yr old, whereas no such associations were observed based on volume of physical activity indicated by conventional activity minute-based metrics (21). Recently, Rector and colleagues (22) reported that greater complexity of daily activity behavior was associated with lower frailty index scores and higher ADL function among geriatric inpatients 65 yr or older. However, daily activity behavior complexity remains sparingly explored, and it is currently unclear whether it is associated with mobility or physical function among older community-dwelling adults.

As alluded to above, it has been recognized that metrics indicating patterning of daily activity in addition to quantifying

volume of activity (e.g., minutes per day spent in moderate to vigorous activity) could be useful (11,23,24) particularly among older populations (11). As body-worn sensor technology is becoming more prevalent, they could be used to continually track and monitor changes in mobility and physical function in older adult population and, hence, enable the detection or prediction of adverse and deleterious decline. Metrics based on pattern analysis have already been demonstrated as more sensitive than volume of activity to changes in clinical and functional characteristics (10,14,21,25,26). Physical task fatigability, for example, seems to be more sensitively indicated by fragmentation of daily activity behavior pattern compared with activity minutes (25,26). Moreover, it is thought that it suffices to break a continuous bout of sedentary behavior with a brief bout of low-intensity activity to gain positive health effects (27). Such brief bouts may not register in the activity minutes but would increase the complexity of daily activity behavior because of the changes between activity states (e.g., an activity to rest transition) (10,14,20).

Building on such findings, we hypothesize that daily activity behavior pattern complexity could capture meaningful characteristics of daily activity and thus warrants further exploration. Therefore, the purpose of the present study was to explore the association between the complexity of daily activity behavior pattern and the mobility and physical function among community-dwelling older adults 75, 80, or 85 yr of age. We hypothesized that a positive association exists between the complexity of habitual activity pattern and the mobility and physical function.

METHODS

This was a cross-sectional cohort study of community-dwelling 75-, 80-, and 85-yr-old men and women living in the city of Jyväskylä, Central Finland region. The participants were visited at their homes by a trained research assistant who attached an accelerometer on the trunk and on the thigh to be worn for at least 7 d before attending a testing session at the University of Jyväskylä, Finland. The protocol (28) and a detailed recruitment flow chart have been published (29), but pertinent details are provided in the present article as well.

Participants. The sample for the present study forms a part of the “Active aging—resilience and external support as modifiers of the disablement outcome” (AGNES) cohort study (28). In brief, all 75- to 85-yr-old individuals living in Jyväskylä, Finland, in 2017 and 2018 were identified from the population register and invited to take part in the AGNES cohort study with a letter and a subsequent phone call. The inclusion criteria were age based on year of birth, living independently in the recruitment area, and consent to take part. Exclusion criteria were unwillingness to participate or inability to communicate. A total of 309 participants with concurrent thigh- and trunk-worn accelerometer wear for at least three consecutive days were included in the present study (Fig. 1).

The study was conducted in agreement with the Helsinki declaration, informed written consent was obtained from all

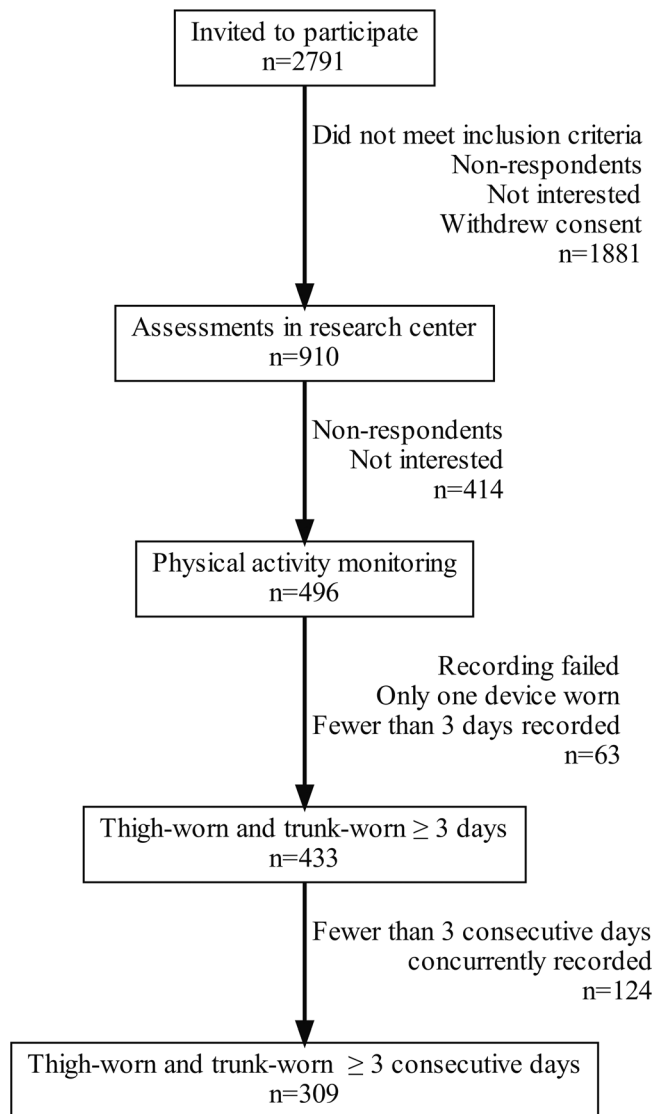


FIGURE 1—Flow chart of the study recruitment.

participants, and Central Finland Health Care District provided an ethical statement of the study (August 23, 2017).

Protocol. As described in the AGNES cohort protocol (28), the participants were asked to wear two triaxial accelerometers (both sampling continuously at 100 Hz, 14-bit $\pm 16g$, eMotion Faros 180, Bittium Corporation, Oulu, Finland, and 13-bit $\pm 16g$, UKK RM42, UKK Terveyspalvelut Oy, Tampere, Finland) for 7 to 10 d before attending a laboratory gait assessment at the University of Jyväskylä, Finland, campus. The participants were visited at their home by the study staff, and the accelerometers were taped on the participant's body using a rectangular patch of transparent adhesive film. A wound patch was folded and placed underneath the accelerometer to minimize skin irritation during wear. The eMotion Faros 180 sensor could only record for 4 d continuously and was swapped on the third to fifth wear day by the study staff at the participant's home. The two records were concatenated to provide more than 4 d of continuous wear. The eMotion Faros 180 sensor

was attached on the sternum or diagonally on the left side of the chest under the breast if sternum was uncomfortable for the participant. The UKK RM42 sensor was attached on the anterior aspect of the mid-thigh of the jumping leg (or kicking leg or the side of the dominant arm, if the participant was unable to identify their jumping or kicking leg).

The laboratory testing session included measuring height with a stadiometer to the nearest 0.5 cm and body mass with an electronic scale to the nearest tenth of a kilogram. The session gait assessment included a modified 6-min continuous walking test up and down a 20-m track in a corridor. The modification compared with the typical instruction of requesting to walk as far as you can was to request to walk at the preferred pace (28). The distance covered in the 6-min walking test is reported as an indicator of physical function.

The home visit included a testing session. Life-space mobility (University of Alabama at Birmingham Study of Aging Life-Space Assessment [7]) was assessed and is reported as a mobility outcome (scores from 0 to 120). Cognitive ability was assessed using the Mini-Mental State Examination (30) and is reported as a descriptive characteristic (scores from 0 to 30). Lower extremity physical function was assessed with the Short Physical Performance Battery (31) and is reported as an indicator of lower extremity physical function (scores from 0 to 12). Higher scores indicate better performance on all the above assessments conducted at the participant's home.

Numerical analysis and posture and activity state estimation algorithm. The triaxial accelerations recorded by the two concurrently worn accelerometers were processed identically; the resultant acceleration was first calculated for each sampling instant, and the mean amplitude deviation (MAD) (32) based on the resultant was subsequently calculated for nonoverlapping 5-s epochs. The mean values of the x , y , and z accelerations were also noted for the same epochs, and the 5-s epochs were assigned the real-time time stamp of the first data point included into a given epoch.

The device records were aligned temporally, and the posture of each 5-s epoch was subsequently estimated as follows (for further details and for algorithm validity, see Appendix 1, Supplemental Digital Content 1, <http://links.lww.com/MSS/C536>):

- lying if both devices indicated angle $>\pi/4$
- sitting if thigh indicate angle $>\pi/4$ and trunk indicated $\leq\pi/4$
- upright if both devices indicated angle $\leq\pi/4$

The $\pi/4$ ($=45^\circ$) threshold was adopted from Vähä-Yppä et al. (33). Moreover, upright posture was separated to standing, walking, and activity other than walking based on signal intensities. The upright epochs, which had MAD values between 0.035g to 0.6g and 0.035g to 1.2g for the trunk-worn and the thigh-worn devices, respectively, were assigned to walking (lower than the bottom cutoff on either device remained in standing), and epochs with MAD values $>0.6g$ or 1.2g for the trunk- and the thigh-worn devices, respectively, were assigned into activity other than walking (i.e., higher than the cutoff on either device or on both). These categorizations

resulted in five possible activity states (lying, sitting, standing, walking, or activity other than walking) for each 5-s epoch. The activity state and the time stamps corresponding to the first sample of the given epoch were saved to a file. Only epochs that had concurrent recorded data from both accelerometers were saved. Activity state files with two coarser time grains were created as well, one with nonoverlapping 1-min epochs (the mode of the 12 consecutive 5-s epochs used for a given minute) and another with nonoverlapping 5-min epochs (using the mode of 60 consecutive 5-s epochs).

Daily activity behavior pattern complexity estimation.

The activity state files were explored to identify a continuous recording of at least three consecutive midnight to midnight, and the longest such epoch was chosen for complexity estimation (Fig. 2). Cilibrasi and Vitanyi (34) have shown that Kolmogorov complexity can be estimated as the ratio of uncompressed and lossless compressed signals. However, Kolmogorov complexity is incomputable and hence they used the ratio of Lempel–Ziv compressed signal to uncompressed signal as an indicator of complexity. Their approach was adopted and estimated by compressing the data using a standard file compression package

(java.util.zip package) and by calculating how much the size of the data could be deflated compared with the original file size (Appendix 2, Supplemental Digital Content 1, <http://links.lww.com/MSS/C536>). The resulting deflation ratio is a metric of the daily activity behavior pattern Lempel–Ziv complexity (34) and is reported as the outcome. A high deflation ratio indicates a less complex pattern. The same complexity estimation was repeated thrice for each participant, once per temporal grain, i.e., for the 5-s, 1-min, and 5-min epochs.

Statistical analysis. The AGNES study sample size was based on statistical sensitivity analysis and designed to enable detecting linear regression with at least 5% of the variation explained after accounting for 10 covariates. All individuals with any valid data from the AGNES study were included in the present examination. The number of individuals considered for each statistical test was decided independently from the other tests, which resulted in the number of participants included in a particular test to vary between tests. That is, missing a result in one test did not lead into excluding the participant from another test. The number of participants considered for a particular test is given in the Tables 1 and 2.

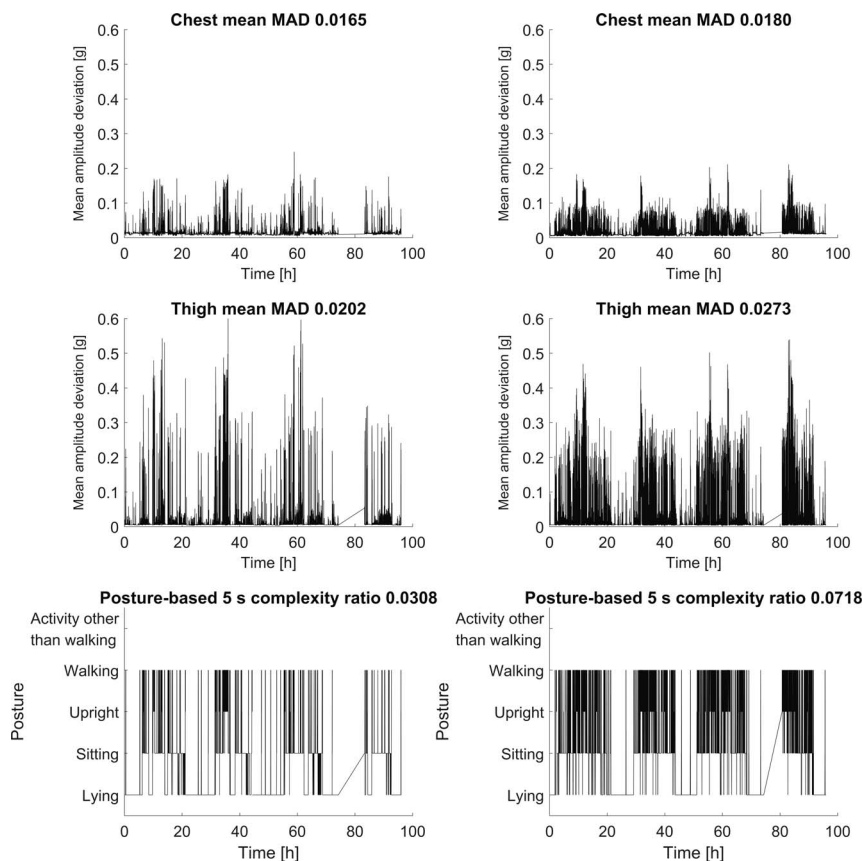


FIGURE 2—Two samples of the signals used for Lempel–Ziv daily activity behavior pattern complexity estimation. (*Left panel*) A participant from the bottom 5 in terms of daily activity behavior pattern complexity. (*Right panel*) A participant from the top 5 in terms of daily activity behavior pattern complexity. Two accelerometers were worn concurrently (thigh, chest), and posture (lying, sitting, upright) was deduced based on sensor orientations in 5-s nonoverlapping epochs. Upright activities were categorized as upright, walking, or activity other than walking based on the MAD of the epoch. This resulted in five possible physical behavior states for each of the 5-s nonoverlapping epochs. Lempel–Ziv daily activity behavior pattern complexity was calculated as the ratio of the “deflate” compression algorithm compressed byte length to the uncompressed byte length. Note the gap in the data sets between at around the 70 to 80 h. This corresponds to the battery of the chest-worn device running out and being replaced by a charged device to enable more than 3 d of monitoring. The wear periods were concatenated for complexity analyses.

TABLE 1. Descriptive characteristics, cognitive, and functional performance indicators by sex.

	Men,		Women,	
	Men, <i>N</i>	Mean ± SD	Women, <i>N</i>	Mean ± SD
Age (yr)	130	78.2 ± 3.4	179	78.2 ± 3.4
Height (cm)	130	173 ± 7	179	158 ± 5
Body mass (kg)	130	79.2 ± 11.6	179	69.8 ± 12.6
10 m walk (s)	130	8.09 ± 2.83	179	8.23 ± 2.12
MMSE (score)	130	27.2 ± 2.5	179	27.6 ± 2.5
SPPB (score)	130	10.5 ± 2	179	10.3 ± 1.9
6-min walk distance (m)	123	444 ± 82	173	415 ± 74
Life-space mobility (score)	130	79.9 ± 18.3	179	69.6 ± 17.3

N, number of participants; MMSE, Mini-Mental State Examination; SPPB, Short Physical Performance Battery.

The average and dispersion characteristics of the sample were computed and are reported as mean followed by SD in parentheses. Some variables were not normally distributed, and transformations did not result in normalization of distribution. Therefore, nonparametric statistical methods were chosen. Deflate ratios were compared between sexes (male and female) and age-groups (75, 80, and 85 yr) using robust ANOVA (raov from the “Rfit” package). *Post hoc* tests of deflate ratios between sex and age-groups were evaluated using two-sample Wilcoxon rank sum tests (wilcox.test from the “stat” package) where appropriate. The association between daily activity behavior pattern complexity and mobility and physical function was estimated using Spearman rank correlation, and the analyses were stratified by sex. Moreover, to examine whether daily activity behavior pattern complexity measures were associated with mobility and physical function independent of age, sex, and average daily physical activity, linear regression models were run as sensitivity analyses. Before entering the data to the model, logarithm transformation was applied to all variables to normalize the data. In the linear regression models, the associations between the complexity of activity behavior pattern and the mobility and physical function were adjusted first for age and sex. After that, daily average acceleration volume (*g*) obtained from the eMotion Faros 180 sensor was added in the model. Significance level was set at $P \leq 0.05$. Statistical analyses were conducted using R (64-bit, version 3.6.3, <https://www.r-project.org/>) and SPSS version 26.

TABLE 2. Complexity (deflate ratio) of daily activity behavior pattern analyzed with three different temporal coarseness scales (nonoverlapping 5-s epochs, 1-min epochs, and 5-min epochs) by age-group and sex.

Coarseness Scale	Age-Group	Men,		Women,	
		Men, <i>N</i>	Mean ± SD	Women, <i>N</i>	Mean ± SD
Deflate ratio 5 s	75	69	0.0489 ± 0.0106	95	0.0515 ± 0.0101
	80	40	0.0491 ± 0.0109	53	0.0502 ± 0.0101
	85	21	0.0442 ± 0.0115	31	0.0468 ± 0.0096
Deflate ratio 1 min	75	69	0.0982 ± 0.0145	95	0.0946 ± 0.0135
	80	40	0.0970 ± 0.0155	53	0.0940 ± 0.0146
	85	21	0.0912 ± 0.0157	31	0.090 ± 0.0145
Deflate ratio 5 min	75	69	0.163 ± 0.022	95	0.155 ± 0.02
	80	40	0.161 ± 0.021	53	0.159 ± 0.021
	85	21	0.158 ± 0.021	31	0.154 ± 0.018

Statistical comparisons given in text.
N, number of participants.

RESULTS

Descriptive characteristics and physical function indicators of the sample are given in Table 1. Participant numbers for the various characteristics measured in the present study varied from 123 men and 173 women (6-min walking test) to 130 men and 179 women (the full included sample).

Daily activity behavior pattern complexity analyzed in the three temporal grains divided by age-group and sex is given in Table 2. A significant age effect was indicated by the robust ANOVA testing for the 5-s and 1-min temporal grains ($F = 3.48$ to 5.17 , $P = 0.006$ to 0.032) but not for the 5 min grain ($F = 0.88$, $P = 0.42$). None of the temporal grains indicated a significant sex effect ($F = 1.65$ to 3.85 , $P = 0.051$ to 0.20) or age–sex interaction ($F = 0.002$ to 0.87 , $P = 0.42$ to 1.00). *Post hoc* testing between age-groups indicated no difference between the 75- and the 80-yr-old groups, but the 85-yr-old group had 5% to 9% lower behavior complexity compared with both younger age-groups in the two finest temporal grains ($P = 0.002$ to 0.040).

Age-groups were pooled for correlation analyses, and the correlation matrix between daily activity behavior pattern complexity with the three temporal grains and mobility and physical function indicators by sex is given in Table 3. The finest temporal grain (5 s) showed weak positive associations between complexity and mobility and physical function indicators in both men and women; however, with the coarser grains, the weak positive associations were only observed in men in the 1-min grain and in neither sex with the coarsest grain (5 min).

We explored the linear regression analyses as sensitivity analyses because of the significant age effect observed in complexity. Also, it was *a priori* well established that an age dependence exists in physical function and mobility. The observed associations remained evident after adjusting for age and sex. However, after adjustment of daily average acceleration volume the potential associations between complexity and outcomes of physical function or mobility vanished (see Supplemental Tables 1–4, Supplemental Digital Content 2, <http://links.lww.com/MSS/C537>).

DISCUSSION

The primary finding of the present study was that a weak positive association was observed between mobility, indicators

TABLE 3. Spearman rank correlation coefficients between complexity (deflate ratio) of daily activity behavior pattern analyzed with three different temporal coarseness scales (nonoverlapping 5-s epochs, 1-min epochs, and 5-min epochs) and mobility and physical performance by sex.

Variable	Deflate Ratio 5 s		Deflate Ratio 1 min		Deflate Ratio 5 min	
	Men	Women	Men	Women	Men	Women
SPPB	0.20*	0.18*	0.13	0.06	0.02	-0.13
6-min walk	0.31***	0.20**	0.19*	0.08	0.12	-0.06
Life-space assessment	0.27**	0.22**	0.23**	0.14	0.13	0.06

* $P \leq 0.05$.

** $P < 0.01$.

*** $P < 0.001$.

SPPB, Short Physical Performance Battery.

of physical function, and daily activity behavior pattern complexity assessed with the two finer temporal grains. Although the associations were categorized as weak in terms of statistical significance, the strengths of the associations are comparable with those observed, e.g., between volume of daily physical activity and life space (8) or physical function (35). These findings are, generally speaking, in agreement with previous research related to the association between the complexity of activity behavior pattern and the physical function and mobility assessment. Previous research has indicated that more complexity and larger life space are positively associated with physical function (8,9,14,21). Only a fine temporal grain of 1 s (10,14,21) has been used previously. The 1-s grain is finer than the finest grain of 5 s used in the present study. We extended the analysis to coarser grains and found that only grains up to 1 min in duration were associated with indicators of mobility and physical function. The finer temporal grains would capture phenomena with a relatively high temporal precision, including brief bouts of ambulation, whereas the coarser grains would only register more prolonged bouts of behavior effectively averaging out any brief intermissions. Considering the fragmented nature of daily activity behavior found among older individuals (25,26), and the potential of brief breaks in sedentary behavior to have positive health effects (27), we postulate that the finer temporal grains may have better pragmatic utility compared with the coarser grains.

Positive associations between life-space assessment and daily activity behavior pattern complexity were observed at the two finest temporal grains. The finding is concordant with the theoretical concept we argued in the introduction. That is, one would expect mobility and behavior complexity to be linked because larger mobility indicates farther travel from home compared with smaller mobility (7). Travel, in turn, necessitates ambulation (9) and capacity to alter motor behavior to adapt to different task demands (13), which will be reflected in the richness of activity states. Therefore, more travel targets are likely to be observed as higher complexity compared with fewer travel targets. Moreover an age-group effect was observed in daily activity behavior pattern complexity, which is in concordance with the effect of aging on physical function and performance (2). The loss of complexity not only in physiological but also in behavioral time series has been suggested to be a potential indicator of lower physical resilience (12,22), a topic that warrants further investigation. Sensitivity analyses indicated that daily activity behavior pattern complexity was no longer an independent predictor of life space or physical function when total volume of activity was included as a covariate. Engaging with additional changes in activity states likely mandates an increased volume of activity in the present study cohort compared with fewer activity state changes. Nevertheless, we hypothesize that there are outcomes not tested in the present study that could be predicted by daily activity behavior pattern complexity independent of activity volume, e.g., on the findings reported by Zhang et al. (21).

Overall, the findings are congruent with the literature related to previous research into daily behavior complexity.

Paraschiv-Ionescu and colleagues (14) have reported a lower level of complexity among those with higher level of fear of falling than those with a lower level of fear of falling. However, whether complexity measures provide added value to the conventional activity metrics requires more investigation. Zhang et al. (21) reported subtle behavior change indicated by complexity measures but not captured by total activity volume (e.g., step count) in association to an exercise intervention with 60- to 70-yr-old participants. However, the sensitivity analyses of the present study showed that the associations of complexity measures with life space or physical function measures were explained by the daily average acceleration, which indicates total activity volume. Complexity estimates at all three coarseness grains were positively associated with the total average acceleration in the present study (see Supplemental Tables, Supplemental Digital Content 2, <http://links.lww.com/MSS/C537>), which likely explains the lack of explanatory power for complexity after inserting the daily average acceleration into the model. Considering both the present and the findings reported by Zhang and colleagues (21), we claim that the role of complexity in addition to total activity volume in describing daily activity behavior pattern remains ambiguous. It remains plausible that daily activity behavior pattern could, for example, provide meaningful information regarding cognitive processes associated with planning the day (36,37) or be indicative of impending functional decline.

Regarding the temporal grain exploration, prior art by Zhang and colleagues (21) implemented temporal grain exploration by smoothing their 1-s state vector before undertaking complexity assessments. They showed that both the complexity estimates based on unfiltered and the smoothed states were sensitive to a 4-wk home-based exercise intervention but that the smoothed estimates seemed to be preferable over the unfiltered ones (21). The present research extended the previous work by using a 5-s epoch and by also exploring much coarser temporal grains as well. We found that the finest 5-s grain was best associated with the explored variables, and interpreted in accordance with the literature, it seems that it may be reasonable to use such a fine temporal grain for behavior complexity assessments. Most of the aforementioned studies have used Lempel–Ziv complexity, which is simple to implement and has been demonstrated to be associated with various pragmatic outcomes: fear of falling (14), chronic pain (10), exercise intervention (21), and mobility and physical function in the present study. Taken together, we postulate that Lempel–Ziv complexity provides a reasonable marker of daily activity behavior pattern complexity and that a fine temporal grain between 1 and 5 s is likely a reasonable choice.

Shiroma and colleagues (11) have highlighted that further potential for extracting meaningful insight into daily activity behavior pattern based on prolonged accelerometry records exists among older individuals. The complexity evaluation approach introduced by Paraschiv-Ionescu and colleagues (10) and adopted in the present study could be particularly powerful in providing continuous monitoring of mobility and daily activity behavior pattern in older adult population as body-worn

devices are becoming more readily available. This could enable the early detection or prediction of potential deleterious decline in mobility and physical function. This approach is particularly suited to older adults and highly sedentary populations as their daily activity behavior pattern is dominated by bouts of sedentary behavior and the complexity metrics are reflective of change in activity states. A closely related concept, activity fragmentation, has been suggested and shown to have pragmatic utility (25,26). The difference between complexity analysis and fragmentation analysis is the inclusion of recurrence and intensity in the complexity consideration. That is, fragmentation analysis uses only two states (active/inactive) and does not consider the temporal patterning of the states (26), whereas complexity has multiple states (five in the present study) and does consider the temporal patterning of states. The Pearson correlation coefficient between fragmentation and 1-min temporal grain was $r = 0.17$ to 0.29 for men and women, respectively, in the present data set (data not shown; fragmentation results reported by Palmberg et al. [25] and a 1-min epoch was used for the fragmentation analyses). It remains to be explored whether complexity adds valuable insight over that provided by fragmentation.

It needs to be pointed out that approaches other than Lempel–Ziv complexity have been tested in the literature. Raichlen and colleagues (38) assumed that daily activity behavior pattern has fractal characteristics and subsequently assessed fractal complexity using detrended fluctuation analysis (38). Rector and colleagues (22) used multiscale entropy slope as an indicator of behavior complexity. For completeness' sake, we tested both detrended fluctuation analysis and multiscale entropy slope on the 5-s epoch data, and the results are provided in Supplemental Table 5 (Supplemental Digital Content 2, <http://links.lww.com/MSS/C537>). Detrended fluctuation analysis considers a markedly longer time scale than any of the coarseness scales used in the present study (38). By contrast, multiscale entropy slope works on time scales similar to those tested in the present study but captures different characteristics of the signal compared with Lempel–Ziv complexity (22). The various metrics of complexity describe different aspects of the recorded signal, and we would therefore not recommend one over the others as a one size fits all indicator of daily activity behavior pattern complexity.

When interpreting the findings, it should be kept in mind that the cross-sectional study design does not allow establishing causality. Moreover, only three temporal grains for complexity estimation were explored and different coarseness

scales could plausibly indicate different aspects of physical behavior. In addition, daily activity behavior states were based on accelerometry signal and limited to only five categories, which may hide meaningful nuance from the underlying physiological state. Hence, it might be worth applying complexity analysis to raw accelerometry signals or, for example, on 1-s epoch intensity summaries. The delimitations were applied to limit the computational expense of the analyses to a feasible duration. As a result, a large analysis parameter space remains unexplored. Furthermore, the findings may not generalize to a population with a more diverse ethnic composition and/or to younger age-groups. In addition, we were unable to explore potential age-related systematic bias caused by age-related decline in movement velocities (15). Aside from the limitations and delimitations, the strengths of the study included the population representative sampling, the exploration of multiple temporal coarseness scales, and the assessment of daily activity behavior pattern in the habitual environment.

CONCLUSIONS

In conclusion, the presented simple-to-compute complexity metric presents a potentially informative assessment of daily activity behavior pattern. Lempel–Ziv complexity with a fine temporal coarseness seems to provide a reasonable marker of daily activity behavior pattern complexity among community-dwelling older adults.

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Ti. R., K. K., E. P., Ta. R., L. P., L. K., and S. C. contributed to the concept and design. Ti. R., E. P., Ta. R., L. P., and L. K. performed data collection. Ti. R., K. K., E. P., Ta. R., L. P., L. K., and S. C. analyzed and/or interpreted the data. T. R., K. K., E. P. and S. C. drafted the article. Ti. R., K. K., E. P., Ta. R., L. P., L. K., and S. C. performed critical revision of the article. All authors approved the article.

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