

Using Consumer Wearables to Measure Physical Activity of Nursing Home Residents with Dementia

Daniela Gawehns MSc^{1*}, Suzanne Portegijs MSc²,
Adriana Petronella Anna van Beek PhD², Matthijs van Leeuwen
PhD¹

^{1*}LIACS, Leiden University, Niels Bohr Weg 1, 2333 CA, Leiden, The Netherlands.

²NIVEL, Otterstraat 118, 3513 CR, Utrecht, The Netherlands.

*Corresponding author(s). E-mail(s): gawehnsd@liacs.leidenuniv.nl;
Contributing authors: s.portegijs@nivel.nl; svanbeek@verenso.nl;
m.van.leeuwen@liacs.leidenuniv.nl;

Keywords: wearables, activity estimation, nursing home, dementia

Abstract

Physical activity of nursing home residents can be assessed with tools such as questionnaires and standardized fitness tests. For residents with dementia, however, those tools can be cognitively challenging and difficult to administer. Consumer wearables could potentially aid as an affordable tool for ubiquitous assessment. In this pilot study with 16 participants, we explore how measurements with an off-the-shelf wearable relate to structured observations of physical activity. We collected both processed and raw tri-axial accelerometer data from Samsung, wrist-worn fitness trackers. To anchor those data in the free living environment, we compare the measurements with the physical activity scale of the Medlo behavioral observation scheme. We show that consumer wearables are a valid tool for long term data collection in this vulnerable patient population. Regarding the movement intensity, the data collected by fitness trackers is overall in accordance with the data collected with the observational tool. Regarding

the type of movement, we conclude that the automatic activity classification on the wearables is not yet ripe for use in a mostly sedentary patient population.

Introduction

Physical activity (PA) of nursing home residents is researched in the context of increasing health outcomes and wellbeing [1]. Examples are the association of PA with sleep [2], number of falls [3], or energy expenditure and intake [4]. Dementia and PA influence each other. Depression and apathy might manifest in passivity and low PA, while restless behaviors will manifest as higher PA [5]. Any measurement tool for PA will hence have to be able to account for a large range of activity levels. Additionally, residents with dementia have more non-psychiatric comorbidities than other residents [6]. Comorbidities affecting the heart function might make PA estimation based on heart rate less reliable if they are not taken into account. As in other geriatric patient populations, any measurement tool will have to account for the use of walking aids, such as walkers or canes.

Here, we report on the feasibility and the limitations of measuring PA with a consumer wearable in a Dutch nursing home. The presented data were collected as part of a research project that assessed the impact of providing unobstructed access to green spaces to residents with dementia. The main research question was how more access to green spaces affects the residents' quality of life, as well as the embedding of dementia care in the local community. We therefore assessed PA of the residents with different measurement tools and collected data on how people used the park of the nursing home with sensors and observations.

Commonly used assessment tools for PA of nursing home residents without cognitive impairment can be divided into three categories: observations of functional fitness tests, questionnaires, and technical measures [1]. The first two types of tools require the participant to understand and follow instructions. For residents with dementia, this might pose a problem if the test is performed at the wrong moment, e.g. after a troubling experience for the resident. Furthermore, a participant's willingness to cooperate can fluctuate by day and time of the day. Achieving a consistent assessment is hence difficult with one-point-in-time measures.

Technical measures, on the other hand, come with fewer and simpler instructions. According to Wootten et al.'s [1] categorization, technical measures include tests with sensing technology for grip and muscle strength, body composition tests, as well as assessment with accelerometers.

Wearable accelerometers have been used to estimate sleep and PA of nursing home residents with dementia before [7]. According to Cote et al.'s review from 2021, studies in nursing homes used wearables built for laboratory settings (e.g., Actigraph, Actiwatch). For our study, we opted for a consumer-grade fitness watches as they were not only cheaper, but also designed for durability in daily life, which was an important requirement from the nursing staff. Furthermore, they are often

outfitted with more sensors, such as magnetometers, barometers or GPS receivers. Those additional sensors collect useful data for activity recognition methods [8]. The option of tracking location outside by GPS was used to assess the use of green spaces by residents in another part of the study.

To anchor the sensor data in real life observations, we used data collected with the Medlo observational tool. The Medlo tool [9] was developed to capture daily life activities of residents in nursing homes and day care centers. Observations are logged per minute in 30-min sessions and observers use an observation sheet covering four dimensions of daily life activities in seven variables: Activities (type, engagement, physical activity), Physical Environment (location, interaction with environment), social interaction (occurrence, type, interaction partner), and emotional well-being (mood, agitation). For the aim of this paper, we focused on the variable "physical activity", which is scored on a 7-point Likert scale.

We used Samsung, off-the-shelf fitness wristbands with our own data collection app [10] to record accelerometer and barometer readings, and GPS location information. Additionally, we recorded manually the "24hrs log" of the watch, which are movement categories that are calculated and displayed on the device (low activity, medium, high activity, sleep, run, swim, cycle). We wanted to find out if those movement categories are useful in a mostly sedentary patient population. Furthermore, we wanted to compare PA estimates based on raw accelerometer with the modeled movement categories and observed activity levels.

Materials and Methods

Study Design, Setting and Participants

We report the results of a prospective and observational study.

This study is part of the project "Dementia back in the heart of society - a complex case study". In this project, the impact of a renovation of a nursing home and reorganization of the care management on residents, staff and family members were assessed. We are presenting here tools used within the study protocol to assess PA of nursing home residents. The data collection for the overall project was in fall 2018, spring 2019, spring 2021 and fall 2021. In this paper, we present data collected in spring 2021.

For the overall project, participants were recruited in two waves in 2019 and in 2021. All residents with a diagnosis of dementia were invited to join the study by a letter to their legal representatives. In spring 2021, 54 residents were invited, leading to a 26 participants consenting to participate in the study. Unfortunately, due to informed consent letters reaching us too late, we only managed to collect the following data: for 12 participants, we collected both wearable and observational data; for 4 participants, we collected only wearable data and for one participant only observations. Participants were between 72 and 91 years old on the day of data collection (Mean: 82, SD:

5.3 years). Overall, 15 women and 1 man participated in the data collection with the wearables.

Ethics

The study protocol was approved by the Ethics Review Board at Utrecht Medical Center (protocol 18-127). The legal representatives of all potential participants received a letter explaining the goal of the data collection and the types of data that were to be collected: Observations, Questionnaires, Medical Records, Wearables and Interviews. They could consent to all data being collected or just parts of the data collection.

While collecting data on site, all research assistants and present nursing staff were instructed to remove wristbands as soon as residents requested this or were visibly bothered by it.

To safeguard the participants' privacy, all data was exclusively stored on the smart-watches themselves and on the researchers laptops. None of the collected data was shared with a third party or the watch manufacturer.

Preprocessing and Variable Selection

Wearables We adjusted the settings of the wearables based on the expected participants' characteristics and set the watches to: gender "female", birthdate 1st January 1935, height 170 cm and weight 65 kg. We refrained from setting the watches to the true participant characteristics as this would not only prolong the exchange moment of the watches but is also prone to errors as we kept rotating the watches between participants. We followed the residents' wishes regarding which wrist they wanted to wear the wristband on.

Data from the wearables were collected with our own software and manually. Our software "WEARDA" [10] saved accelerometer data, barometer data and GPS recordings. The data were saved in .txt files on the watches and downloaded from the watches onto the researchers' computer. No cloud storage service or other third party was involved while storing and processing the data. Data of the app called "24 hrs log" were copied manually directly from the watch onto a data collection sheet on a research computer.

From the collected wearable data, we used the accelerometer data and the "24 hrs log" data to estimate activity levels. The "24-hrs log" records per minute the activity intensity as estimated by a Samsung-owned algorithm. The categories are: "not on wrist", "sleeping", "inactive", "light", "heavy", "biking" and "running". Per resident, we created seven data points analogue to the seven categories by summing up the minutes spent per category. Because not all residents had the same wear time of the wristband, we divided the count by wear time in minutes and multiplied it by 30 min to standardize it.

Accelerometer data were collected at 100 Hz. Analogue to previous studies ([11]), we chose to calculate the Mean Amplitude Deviation (MAD) metric over 5 second

intervals and to derive several summary parameters from those data. The MAD is a measure of movement intensity and calculated based on the magnitude of acceleration within a predetermined interval [12]. We calculated the following measures from the MAD: mean (MADmean), standard deviation (MADsd), median MAD (MADmedian) and 95th percentile of MAD (MADqant). Furthermore, we calculated per participant the time spent above 100 milligravitational units (MADrel), and the fragmentation rate of the MAD (MADfrag). The fragmentation rate is the standard deviation of the first derivative of the MAD time series and is an indicator for intensity changes of PA, with a higher value indicating more changes.

Structured Observations To ground the physical activity estimates from the wristbands, we used the PA scale of the Medlo observational tool [9]. The PA scale is an ordinal, 7-point Likert scale. Per observed minute, the research assistant notes the observed movement category. The movement categories are: ML01 = lying/no movement, ML02= sitting quietly, ML03= light to moderate sitting, ML04= standing, ML05= standing activity/ walking around, ML06= walking activity/ cycling, ML07= sports/whole body movement.

In a related study, we checked for interrater reliability of observed activity classifications and found that the collected data matched in 91% of the registered activities [13]. The data were transformed into seven data points per resident, by summing up the minutes a resident spent per category. Analogue to the "24 hrs log" data, we divided the sums per category by the total observation time and standardized it to 30 min.

Summary Statistics

For both the Medlo and the 24hrs categories, we see mainly sedentary behaviors. Residents spent most time in the categories "inactive" for the wearable categories (Fig.1) and "sitting quietly" for the Medlo (Fig.2). The wearables detected approximately the same amount of "light" activity than the Medlo observations of "ML04 = standing" and "ML05 = walking" combined.

We collected almost no observations for the Medlo categories ML03 = "sitting moderate", ML06= "active walk" and ML07= "sports/full body movement" as well as for the 24hrs categories of "heavy", "biking" and "running". We therefore removed those variables from further analysis.

The MAD has an overall mean of 11.15 milligravity units (range: 4.5 to 20.4 milligravity units). This is in accordance with Bakrania et al. [12] who found a mean between 6 and 12 milligravity units (depending on the device) in their sample for sedentary behaviors.

Correlation analysis

We correlated all variables with each other after preprocessing the raw data. The correlation matrix in Fig. 3 is sorted by hierarchical clustering using the complete linkage method. The clusters show clearly that the MAD derived metrics correlate somewhat positively with the more active categories of the Medlo and the "light" activity of the watches' activity classification. There is also a positive correlation with

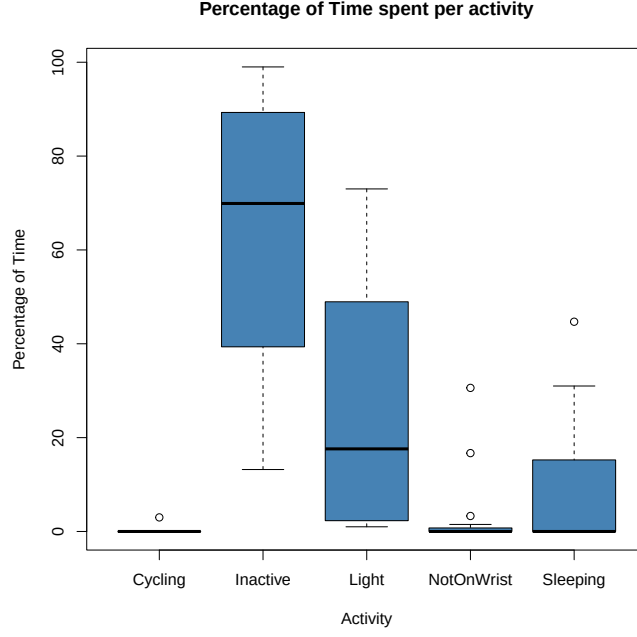


Fig. 1 Boxplots of the collected 24hrs data of all participating nursing home residents ($N = 16$). Per activity, we plotted boxplots of the percentage of measurement time that residents were active in one category.

the category "not on wrist". They correlate negatively with the less active categories of the watches' model (sleeping, inactive) and the Medlo (ML01,ML02).

While all MAD parameters correlate highly with each other, there are differences in association strength with the other variables. The standard deviation and 95th percentile seem to differentiate best between the more active and more inactive Medlo and watch categories. There are larger positive and negative correlations with the watch categories than with the Medlo categories. The directions of the correlations are as expected; positive with the more active categories and negative with the less active categories.

The watches' and Medlo variables also correlate with each other in the expected way. An interesting case is the sleeping and "not on wrist" categories of the watches' model. Those have in general very low correlations with the other activity variables, apart from a positive correlation between Sleeping and Medlo 01 (.66) and between Not On Wrist and Medlo 05 (.65).

Discussion

Our main question was if we can use consumer wearables to estimate activity levels in nursing home residents with dementia, and how those estimations would relate to observational data. The summary statistics confirmed our expectation of a rather

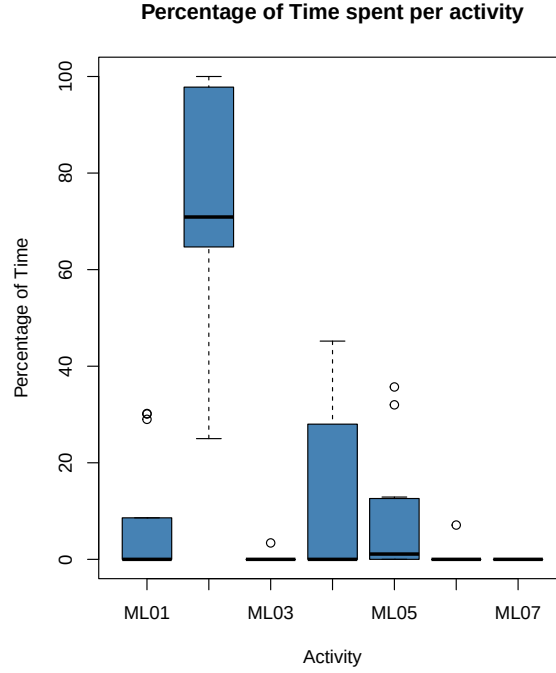


Fig. 2 Boxplots of the collected Medlo data of all participating nursing home residents ($N = 13$). Per Medlo Activity Category, a boxplots shows the percentage of time that residents were active in one category. Categories are: ML01 = lying/no movement, ML02= sitting quietly, ML03= light to moderate sitting, ML04= standing, ML05= standing activity/ walking around, ML06= walking activity/ cycling, ML07= sports/whole body movement

sedentary sample. For the Medlo scores, this is also an artifact of the data collection process, where Medlo observations took place in shared living rooms, which invite residents to sit down and generally do not encourage physical activities. Activities outside the observer’s field of view were registered as “non-observable”, which might cause an underestimation of PA [13]. The wearable data confirm low activity levels over the entire measurement period, which includes time spent outside shared living spaces and outside registered observations. We did not collect data during morning and evening routines, which we would expect to come with a big share of PA, such as walking to and from the living room, moving in and out of bed, and bathroom routines. In future research, one could use wearables during those moments to collect data without breaching residents’ privacy. This would give a more complete picture of the residents’ PA throughout the day.

Overall, the found correlations are according to our expectations, with higher scores on MAD metrics being associated with more time spent in higher activity categories.

We found positive correlations between the MAD metrics and the active Medlo categories (ML04 and ML 05). It is noteworthy that the correlations between the

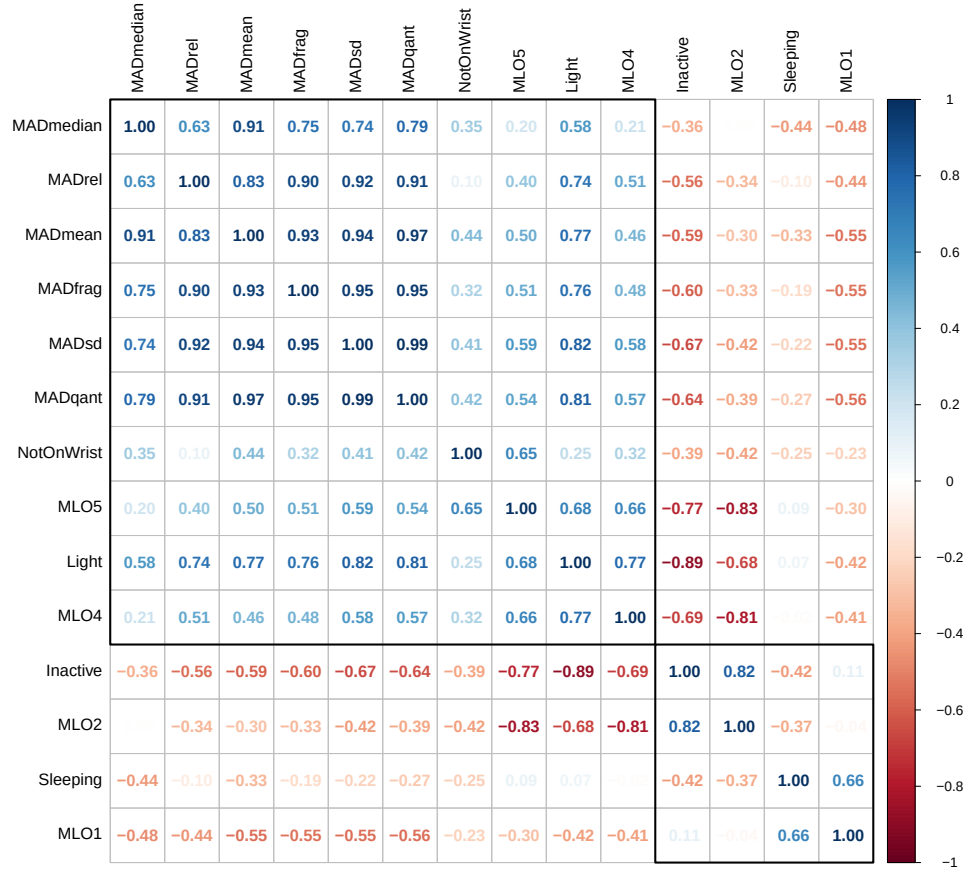


Fig. 3 Correlation matrix of all variables. The correlation matrix is sorted hierarchically, which yields two clusters, one with the MAD derivatives and three active categories plus "not on wrist" and another cluster of the least active movement categories.

watches' "light" activity category and the Medlo categories are more pronounced than the correlations between the MAD metrics and the Medlo categories. In our sample, conclusions based on any of the collection tools will be very similar.

Apart from PA levels, researchers might be interested in how engaged participants are when performing certain activities or in which context the activity takes place. Observational tools can generate such additional information. We argue that PA scores can be estimated similarly well with observations and wearables. A combination of both however would allow researchers to set the results of the observation period into the context of an entire day of PA. Data from wearables can provide this context without having to rely on carers' or residents' memory of that day.

For our analysis, we derived several MAD metrics. From the correlation matrix, we see that there are differences in how those metrics correlate with the activity categories. Especially, the standard deviation and the fragmentation rate seem to differentiate better between categories. We suggest including derivatives for the spread of MAD when using raw accelerometer data in predictive models to increase predictive performance.

We see that sleep has a positive association with the lowest observed activity category (ML01) and is negatively associated with the "inactive" category. We interpret this as the wearable detecting very low activity levels as sleep instead of inactive. The association with the MAD derived features are not very coherent, the negative correlation with the median of the MAD however supports our interpretation. Sleep is often used as an outcome variable in health care research. We argue that for mainly sedentary populations, more validation studies are needed to use commercially available sleep categorizations, as they cannot distinguish well between sleep and very little activity.

The presented data are limited by a rather small sample. However, we collected per person a long interval of movement data with the wearables. This makes the found associations between the watch-derived data points more robust. We would like to point out that the Medlo is not the only observational tool to assess activity levels amongst dementia patients. Any future research should include other tools (surveys, diaries, medical records) to compare the wearable data with and to ground the conclusions drawn based on wearable data.

Conclusion

In this study, we showed that collecting movement data with commercial, consumer-grade wearables in a population of nursing home residents with dementia is possible. The watch allowed us to collect movement data outside shared living spaces and for several hours at a time. The collected wearable data are in general in accordance with the data collected with an observational tool.

The data was collected with a commercial wearable but in a GDPR proof manner, as none of the collected data, nor the settings of the watch was shared with a third party (for example by sending it via a cloud service for access). This opens opportunities for similar research with other vulnerable patient groups.

Using wearables for ubiquitous, long-term assessment of activity levels in a population of dementia patients living in a nursing home is possible and holds many opportunities for assessing PA in real life situations.

Acknowledgments. We thank all participants and staff members for their time and help during the data collection. Research funding for this project was received from ZonMW (Projectnumber: 733050846), the Dutch funding agency for health and medical research.

Declarations and Competing Interests

The authors have no relevant financial or non-financial interests to disclose.

Data Availability Statement

The data availability statement is forthcoming and will be added with the next version of this preprint.

Author Contribution Statement

D.G. wrote the first version of the manuscript. D.G., S.P., A.v.B and M.L planned the data collection and decided which tools to use. D.G. and S.P. were in charge of the data collection. A.v.B and M.L. helped with the interpretation and contextualization of the analysis results. All authors reviewed the manuscript

References

- [1] Wootten, S., Wiseman, N., Harris, N.: Measuring the outcomes for aged care residents' participation in physical activity interventions: A systematic review of randomised controlled trials. *Australasian Journal on Ageing* **41**(2), 165–187 (2022) <https://doi.org/10.1111/ajag.13026> . Accessed 2023-05-15
- [2] Vogel, O., Niederer, D., Wilke, J., El-Rajab, I., Vogt, L.: Habitual Physical Activity and Sleep Duration in Institutionalized Older Adults. *Frontiers in Neurology* **12** (2021) <https://doi.org/10.3389/fneur.2021.706340> . Accessed 2023-05-15
- [3] Diener, J., Rayling, S., Bezold, J., Krell-Roesch, J., Woll, A., Wunsch, K.: Effectiveness and Acceptability of e- and m-Health Interventions to Promote Physical Activity and Prevent Falls in Nursing Homes—A Systematic Review. *Frontiers in Physiology* **13** (2022) <https://doi.org/10.3389/fphys.2022.894397> . Accessed 2023-05-15
- [4] Murphy, J., Holmes, J., Brooks, C.: Measurements of daily energy intake and total energy expenditure in people with dementia in care homes: The use of wearable technology. *The journal of nutrition, health & aging* **21**(8), 927–932 (2017) <https://doi.org/10.1007/s12603-017-0870-y> . Accessed 2023-05-15
- [5] Anderiesen, H., Scherder, E.J.A., Goossens, R.H.M., Sonneveld, M.H.: A systematic review - physical activity in dementia: The influence of the nursing home environment. *Applied Ergonomics* **45**(6), 1678–1686 (2014) <https://doi.org/10.1016/j.apergo.2014.05.011>
- [6] Duthie, A., Chew, D., Soiza, R.L.: Non-psychiatric comorbidity associated with Alzheimer's disease. *QJM: An International Journal of Medicine* **104**(11), 913–920 (2011) <https://doi.org/10.1093/qjmed/hcr118> . Accessed 2023-05-15
- [7] Evaluation of Wearable Technology in Dementia: A Systematic Review and Meta-Analysis **7** <https://doi.org/10.3389/fmed.2020.501104>

- [8] Aguilera, A.A., Brena, R.F., Mayora, O., Molino-Minero-Re, E., Trejo, L.A.: Multi-Sensor Fusion for Activity Recognition - A Survey. *Sensors* **19**(17), 3808 (2019) <https://doi.org/10.3390/s19173808> . Accessed 2023-08-08
- [9] Boer, B., Beerens, H.C., Zwakhalen, S.M.G., Tan, F.E.S., Hamers, J.P.H., Verbeek, H.: Daily lives of residents with dementia in nursing homes: development of the Maastricht electronic daily life observation tool. *International Psychogeriatrics* **28**(8), 1333–1343 (2016) <https://doi.org/10.1017/S1041610216000478> . Accessed 2022-04-04
- [10] Dijk, R.M.K., Gawehns, D., Leeuwen, M.: Wearda: Recording wearable sensor data for human activity monitoring. *Journal of Open Research Software* (2023) <https://doi.org/10.5334/jors.454>
- [11] Schmidle, S., Gulde, P., Koster, R., Soaz, C., Hermsdörfer, J.: The relationship between self-reported physical frailty and sensor-based physical activity measures in older adults – a multicentric cross-sectional study. *BMC Geriatrics* **23**(1), 43 (2023) <https://doi.org/10.1186/s12877-022-03711-2> . Accessed 2023-02-14
- [12] Bakrania, K., Yates, T., Rowlands, A.V., Esliger, D.W., Bunnewell, S., Sanders, J., Davies, M., Khunti, K., Edwardson, C.L.: Intensity Thresholds on Raw Acceleration Data: Euclidean Norm Minus One (ENMO) and Mean Amplitude Deviation (MAD) Approaches. *PLOS ONE* **11**(10), 0164045 (2016) <https://doi.org/10.1371/journal.pone.0164045> . Accessed 2022-11-07
- [13] Portegijs, S., Beek, S., Tuyl, L.H.D., Wagner, C.: Physical activity in people with dementia living in long-term care facilities and the connection with environmental factors and behavior. *Journal of Aging and Physical Activity* **31**(2), 214–222 (2023) <https://doi.org/10.1123/japa.2021-0459>