activAnalyzer
user's guide

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Contents

Section 1

Information

1.1 Assessor

It is possible to provide the name and surname of the assessor. Assessor information must be provided to have a complete document after generating the report at the end of the app.

1.2 Patient

It is possible to provide the name and surname related to the patient, as well as their sex, age, and weight. The user must provide sex, age, and weight information for getting results because these parameters are used to compute basal metabolic rate (BMR) as well as physical activity level (PAL). Patient information must be provided to have a complete document after generating the report at the end of the app.

1.3 Device

It is possible to indicate where the device was placed on the body during the measurement period. Several options are available for the position but for now, the app is designed to work with data recorded at the hip only. Device information must be provided to have a complete document after generating the report at the end of the app. Other relevant information regarding the device (i.e., ActiGraph model, sampling rate, filter enabled when the .agd file was generated from .gt3x data with Actilife® software) are silently captured when uploading the data file.

Section 2

Data uploading, nonwear time detection, and data visualization

The user must upload an .agd file previously generated using Actilife® software with at least the data related to the three axes and to the inclinometer function of the device (time spent in standing, sitting, and lying postures). The length of the epoch used in the .agd file (e.g., 10 s, 60 s) has no importance. Once an .agd file is uploaded, behind the scene, the app reads the file and collapses data to get a dataframe with 1-min epochs thanks to R functions provided in the `actigraph.sleepr` R package (Petkova, 2021). Then, the app computes the vector magnitude ($VM = \sqrt{x^2 + y^2 + z^2}$). After this step, it is possible to configure the analysis to be performed to detect nonwear time. It consists of choosing the activity data (vector magnitude counts or vertical axis counts) and the time interval with zero count to be considered to detect nonwear time, as well as the time interval with nonzero counts allowed during a nonwear period along with the period duration with zero count required back and forward the detected activity to validate nonwear time. The default values provided in the app for configuring nonwear time detection are based on the paper by Choi et al. (2012). Finally, when all inputs are configured as required, the user must click on the "Validate configuration" button. If all inputs are valid, the app detects nonwear time thanks to a function from the `PhysicalActivity` R package (Choi et al., 2021). The app then provides a graphic allowing the user to visualize different data among those contained in the data file. Completing this step is required before going further in the app.

Section 3

Configuration for metrics computation

The user must select an equation to compute METs and the axis and cut-points to be used to compute time spent in sedentary behavior (SED), light physical activity (LPA), moderate physical activity (MPA), vigorous physical activity (VPA), and moderate-to-vigorous physical activity (MVPA).

The equations provided in the app for computing METs can be retrieved from scientific articles:

- `Sasaki et al. (2011) [Adults]` equation (Sasaki et al., 2011).
- `Santos-Lozano et al. (2013) [Adults]` equation (Santos-Lozano et al., 2013).
- `Freedson et al. (1998) [Adults]` equation (Freedson et al., 1998).
- `Santos-Lozano et al. (2013) [Older adults]` equation (Santos-Lozano et al., 2013).

The provided cut-points can also be retrieved from scientific articles:

- Aguilar-Farias et al. (2014) SED cut-points for older adults : $<$200 counts/min [Vector magnitude];
- Sasaki et al. (2011) MPA and VPA cut-points for adults: $\geqslant$ 2 690 counts/min (MPA) and $\geqslant$ 6 167 counts/min (VPA) [Vector magnitude];
- Santos-Lozano et al. (2013) MPA and VPA cut-points for adults: $\geqslant$ 3 208 counts/min (MPA) and $\geqslant$ 8 565 counts/min (VPA) [Vector magnitude];
- Freedson et al. (1998) MPA and VPA cut-points for adults: $\geqslant$ 1 952 counts/min (MPA) and $\geqslant$ 5 725 counts/min (VPA) [Vertical axis];
- Santos-Lozano et al. (2013) MPA and VPA cut-points for older adults: $\geqslant$ 2 751 counts/min (MPA) and $\geqslant$ 9 359 counts/min (VPA) [Vector magnitude].

These cut-points have been recommended by Migueles et al. (2017). However, in the case where none of them would be satisfactory for the user, the app allows to define personalized cut-points.

Finally, this section allows the user to determine the minimum wear time required to get a valid day and the period over which wear time should be obtained during the day. The default value is set to 10 hours (i.e., 600 minutes) over the whole day, as previously recommended (Migueles et al., 2017). To automatically get a recommended configuration (established in COPD patients) in the case where the device would have also been worn during the night (Demeyer et al., 2014), the user can click on the “Set PROactive configuration for 24-h recording” button. Of note, the validation of the whole measurement is left to the appreciation of the user. In the literature, it is commonly accepted to require at least 4 valid days to consider the measurement as a reliable picture of what has been actually performed during a week of measurement. Whatever the number of valid days obtained, keep in mind that one week of measurement may not reflect the average behavior over a longer period of time (e.g., a year).

Once all inputs have been correctly fulfilled, the user must click on the “Run analysis” button. This action triggers several calculations. Firstly, the app computes basal metabolic rate (BMR), based on the sex, age, and weight inputs, and on one of the equations retrieved from the paper by Henry et al. (2005). These equations are shown in Table 3.1.

Table 3.1: Equations for estimating basal metabolic rate

Age category (yr)	Sex	Equation
<3	male	61.0 * weight - 33.7
[3-10[	male	23.3 * weight + 514
[10-18[	male	18.4 * weight + 581
[18-30[	male	16.0 * weight + 545
[30-60[	male	14.2 * weight + 593
[60-70[	male	13.0 * weight + 567
>=70	male	3.7 * weight + 481
<3	female	58.9 * weight - 23.1
[3-10[	female	20.1 * weight + 507
[10-18[	female	11.1 * weight + 761
[18-30[	female	13.1 * weight + 558
[30-60[	female	9.74 * weight + 694
[60-70[	female	10.2 * weight + 572
>=70	female	10.0 * weight + 577

If the patient considers their sex as “undefined,” then an equation for females is used. These equations provide BMR in kcal/day, but the app also silently computes BMR in kcal/min to use it in specific calculations. Then, the following variables are computed for each 60-s epoch of the dataset:

- SED, LPA, MPA, VPA categories based on the axis and the cut-points configured by the user;
- METs, by using the MET equation provided by the user;
- Kilocalories. For non-SED epochs, MET values are multiplied by BMR expressed in kcal/min when using the Santos-Lozano et al. (2013) equations. When using the Sasaki et al. (2011) and Freedson et al. (1998) equations, the MET values are multiplied by weight and 1/60. For SED epochs, BMR expressed in kcal/min is directly used;
- MET-hours related to MPVA, by multiplying the MET value by the time (1/60e of an hour), only when the MET value is $\geqslant 3$.

Once these new variables added to the initial dataset, the app summarizes the results by day using valid wear time only, this for the following metrics:

- `wear_time`: total wear time computed using the daily period defined in the function.

- total_counts_axis1: total counts for the vertical axis.
- total_counts_vm: total counts for the vector magnitude.
- axis1_per_min: mean of the counts per minute for the vertical axis (during the considered wear time only).
- vm_per_min: mean of the counts per minute for the vector magnitude (during the considered wear time only).
- total_steps: total step count.
- total_kcal: total kilocalories.
- minutes_SED: total minutes spent in SED behavior.
- minutes_LPA: total minutes spent in LPA behavior.
- minutes_MPA: total minutes spent in MPA behavior.
- minutes_VPA: total minutes spent in VPA behavior.
- minutes_MVPA: total minutes spent in MVPA behavior.
- percent_SED: proportion of wear time spent in SED behavior.
- percent_LPA: proportion of wear time spent in LPA behavior.
- percent_MPA: proportion of wear time spent in MPA behavior.
- percent_VPA: proportion of wear time spent in VPA behavior.
- percent_MVPA: proportion of wear time spent in MPVA behavior.
- max_steps_60min: best step accumulation per minute averaged over a window of 60 continuous minutes.
- max_steps_30min: best step accumulation per minute averaged over a window of 30 continuous minutes.
- max_steps_20min: best step accumulation per minute averaged over a window of 20 continuous minutes.
- max_steps_5min: best step accumulation per minute averaged over a window of 5 continuous minutes.
- max_steps_1min: best step accumulation per minute over a window of 1 minute.
- peak_steps_60min: step accumulation per minute averaged over the best 60 continuous or discontinuous minutes.
- peak_steps_30min: step accumulation per minute averaged over the best 30 continuous or discontinuous minutes.
- peak_steps_20min: step accumulation per minute averaged over the best 20 continuous or discontinuous minutes.
- peak_steps_5min: step accumulation per minute averaged over the best 5 continuous or discontinuous minutes.
- peak_steps_1min: step accumulation per minute over the best minute (same result as for max_steps_1min).
- mets_hours_mvpa: total MET-hours spent during MPVA behavior.
- ratio_mvpa_sed: ratio between MVPA and SED times (minutes_MVPA / minutes_SED).

Then, the app computes the PAL for each day. To do this, total energy expenditure (TEE) is divided by BMR. TEE is obtained by summing the kilocalories measured during wear time epochs and the kilocalories related to BMR expended during nonwear time epochs (it is assumed that the periods where the device was not worn corresponded to sleeping periods, during which energy expenditure is near of BMR), and by multiplying this sum by 10/9 to take into account the thermic effect of food. Of course, such calculations may conduct to underestimate TEE and PAL if the device was removed during prolonged periods of physical activity. Moreover, even if the device was correctly worn, the estimate of PAL is very approximate since both BMR and kilocalories are estimated using methods that may not be accurate at the individual level.

Finally, the app computes daily averages of the computed metrics using the days considered as valid.

Section 4

Results and export

In the app, the results by day and those averaged using valid days are shown in tables. The user can click on specific buttons to export to .csv files either the marked dataset, the results by day, or the results averaged using valid days. Two last buttons allow the user to generate a report (in either english or french) where all the inputs of the app are recorded, as well as the results. Some comments are provided at the end of the document to help positioning the patient in relation to normative values or guidelines. In the report, some daily results are displayed using figures. This is the case for the PAL, the total number of steps, the times spent in MVPA and SED, and the ratio MVPA/SED. Most of the metrics are also shown for each day of the measurement. The app also provides the PROactive scores related to the amount of physical activity based on the medians of the daily step count and the vector magnitude per minute (Gimeno-Santos et al., 2015). These scores can be useful when the measurement of physical activity was performed in a patient with chronic obstructive pulmonary disease with the goal of using the PROactive tool as described elsewhere (Gimeno-Santos et al., 2015).

Importantly, the comparison of the daily results with normative values or guidelines should be used with caution. Regarding the total number of steps, the values proposed in the figure were obtained using classical pedometers. Be aware of the fact that if the ActiGraph accelerometer that was used was a GT3X generation device, the final result is likely to be underestimated or overestimated in comparison with classical pedometers if the normal filter or the low frequency extension filter was enabled, respectively, when generating the .agd file with Actilife® software.

The daily results for MVPA and SED times are shown in relation to a mortality hazard ratio that has been estimated from accelerometer data (ActiGraph 7164, GT1M and GT3X+ models [normal filter], and the Actical) in +40 yr old adults by Ekelund et al. (2019). In a similar manner, the daily MVPA/SED ratio is shown in relation to a mortality hazard ratio that has been estimated from accelerometer data (ActiGraph 7164 model [normal filter]) in 50-79 yr old adults by Chastin et al. (2021). The statistical information (i.e., hazard ratios and corresponding 95% confidence interval limits) shown in the figures were obtained as follows: first, the web platform WebPlotDigitizer was used to capture the coordinates of several points that constituted the curves showing the hazard ratios and corresponding confidence limits in the original articles. Then, a local polynomial regression fitting procedure was used on the coordinates data in R software. The fitted data were finally used for plotting the figures of the report. Of note, the hazard ratios and confidence limits shown in the figures in relation to the lower and/or upper extremities of the abscissae axis were extrapolated beyond the original data. Importantly, the positions of the patient's results on the curves of the hazard ratios should not be considered as accurate and definitive evidences of patient's health risk, at least for the two following reasons: (i) these curves were established at the population level and are not likely to integrate the multiplicity of the factors that affect health risk at the individual level; (ii) the shapes of these curves are related to specific devices and choices regarding the cut-points defined for SED and MVPA categories and regarding nonwear/wear time analysis. Thus, if the analysis with the activAnalyzer app was performed using an Actigraph model that was different from those used in the studies cited above, and/or with the Lower Frequency Extension filter enabled during the creation of the .agd files, and/or using choices for analyzing data that were different from those made in the studies cited above (different choices could be more appropriate to describe the physical behavior of a specific patient), then the patient's results may be harder to interpret. Rather than comparing patient'results with specific hazard ratios at a precise time point, these figure could be more appropriately used as a pedagogical tool to show the global non-linear effect of physical behavior on health, and to highlight the evolution of the patient' scores over time. For information, the choices made in the studies by Ekelund et al. (2019) and Chastin et al. (2021) are shown in Table 4.1 below.

Table 4.1: Analysis choices made in the Ekelund et al. (2019) and Chastin et al. (2021) studies

Study	**Axis for PA intensity classification**	**SED cut-point**	**MVPA cut-point**	**Nonwear time algorithm**
Ekelund et al. (2019)	Vertical axis	<= 100 counts/min	>= 1952 counts/min	Axis: vertical; Frame: 90 min; Allowance frame: 2 min, stream frame: 30 min
Chastin et al. (2021)	Vertical axis	< 100 counts/min	> 2020 counts/min	Axis: vertical; Frame: 60 min; Allowance frame: 2 min with counts/min <50

References

Aguilar-Farías, N., Brown, W. J., & Peeters, G. M. E. E. (Geeske). (2014). ActiGraph GT3X+ cut-points for identifying sedentary behaviour in older adults in free-living environments. *Journal of Science and Medicine in Sport*, *17*(3), 293–299. https://doi.org/10.1016/j.jsams.2013.07.002

Chastin, S. F. M., McGregor, D. E., Biddle, S. J. H., Cardon, G., Chaput, J.-P., Dall, P. M., Dempsey, P. C., DiPietro, L., Ekelund, U., Katzmarzyk, P. T., Leitzmann, M., Stamatakis, E., & Van der Ploeg, H. P. (2021). Striking the right balance: Evidence to inform combined physical activity and sedentary behavior recommendations. *Journal of Physical Activity and Health*, *18*(6), 631–637. https://doi.org/10.1123/jpah.2020-0635

Choi, L., Beck, C., Liu, Z., Moore, R., Matthews, C. E., & Buchowski, M. S. (2021). *PhysicalActivity: Process accelerometer data for physical activity measurement* (Version 0.2-4) [Computer software]. https://CRAN.R-project.org/package=PhysicalActivity

Choi, L., Ward, S. C., Schnelle, J. F., & Buchowski, M. S. (2012). Assessment of wear/nonwear time classification algorithms for triaxial accelerometer. *Medicine & Science in Sports & Exercise*, *44*(10), 2009–2016. https://doi.org/10.1249/MSS.0b013e318258cb36

Demeyer, H., Burtin, C., Van Remoortel, H., Hornikx, M., Langer, D., Decramer, M., Gosselink, R., Janssens, W., & Troosters, T. (2014). Standardizing the Analysis of physical activity in patients with COPD following a pulmonary rehabilitation program. *Chest*, *146*(2), 318–327. https://doi.org/10.1378/chest.13-1968

Ekelund, U., Tarp, J., Steene-Johannessen, J., Hansen, B. H., Jefferis, B., Fagerland, M. W., Whincup, P., Diaz, K. M., Hooker, S. P., Chernofsky, A., Larson, M. G., Spartano, N., Vasan, R. S., Dohrn, I.-M., Hagströmer, M., Edwardson, C., Yates, T., Shiroma, E., Anderssen, S. A., & Lee, I.-M. (2019). Dose-response associations between accelerometry measured physical activity and sedentary time and all cause mortality: Systematic review and harmonised meta-analysis. *BMJ*, l4570. https://doi.org/10.1136/bmj.l4570

Freedson, P. S., Melanson, E., & Sirard, J. (1998). Calibration of the Computer Science and Applications, Inc. accelerometer: *Medicine & Science in Sports & Exercise*, *30*(5), 777–781. https://doi.org/10.1097/00005768-199805000-00021

Gimeno-Santos, E., Raste, Y., Demeyer, H., Louvaris, Z., de Jong, C., Rabinovich, R. A., Hopkinson, N. S., Polkey, M. I., Vogiatzis, I., Tabberer, M., Dobbels, F., Ivanoff, N., de Boer, W. I., van der Molen, T., Kulich, K., Serra, I., Basagaña, X., Troosters, T., Puhan, M. A., … Garcia-Aymerich, J. (2015). The PROactive instruments to measure physical activity in patients with chronic obstructive pulmonary disease. *European Respiratory Journal*, *46*(4), 988–1000. https://doi.org/10.1183/09031936.00183014

Henry, C. (2005). Basal metabolic rate studies in humans: Measurement and development of new equations. *Public Health Nutrition*, *8*, 1133–1152. https://doi.org/10.1079/PHN2005801

Migueles, J. H., Cadenas-Sanchez, C., Ekelund, U., Delisle Nyström, C., Mora-Gonzalez, J., Löf, M., Labayen, I., Ruiz, J. R., & Ortega, F. B. (2017). Accelerometer Data Collection and

Processing Criteria to Assess Physical Activity and other outcomes: A systematic review and practical considerations. *Sports Medicine*, *47*(9), 1821–1845. https://doi.org/10.1007/s40279-017-0716-0

Petkova, D. (2021). *Actigraph.sleepr: Detect periods of sleep and non-wear from 'ActiGraph' data.* (Version 0.2.0) [Computer software]. http://github.com/dipetkov/actigraph.sleepr

Santos-Lozano, A., Santín-Medeiros, F., Cardon, G., Torres-Luque, G., Bailón, R., Bergmeir, C., Ruiz, J., Lucia, A., & Garatachea, N. (2013). Actigraph GT3X: Validation and determination of physical activity intensity cut points. *International Journal of Sports Medicine*, *34*(11), 975–982. https://doi.org/10.1055/s-0033-1337945

Sasaki, J. E., John, D., & Freedson, P. S. (2011). Validation and comparison of ActiGraph activity monitors. *Journal of Science and Medicine in Sport*, *14*(5), 411–416. https://doi.org/10.1016/j.jsams.2011.04.003