



# Resilience characterized and quantified from physical activity data: a tutorial in R

Supplementary materials:

[www.osf.io/3h7em/](http://www.osf.io/3h7em/)

For correspondence:

[dario.baretta@unibe.ch](mailto:dario.baretta@unibe.ch)

Dario Baretta<sup>1</sup>, Sarah Koch<sup>2,3,4</sup>, Inés Cobo<sup>2,3,4</sup>, Gemma Castaño-Vinyals<sup>2,3,4</sup>, Rafael de Cid<sup>5</sup>, Anna Carreras<sup>5</sup>, Joren Buekers<sup>2,3,4</sup>, Judith Garcia-Aymerich<sup>2,3,4</sup>, Jennifer Inauen<sup>1</sup>, Guillaume Chevance<sup>2,3,4</sup>

<sup>1</sup> Institute of Psychology, University of Bern

<sup>2</sup> Barcelona Institute for Global Health (ISGlobal), Barcelona, Spain

<sup>3</sup> Universitat Pompeu Fabra (UPF), Barcelona, Spain

<sup>4</sup> CIBER de Epidemiología y Salud Pública (CIBERESP), Madrid, Spain

<sup>5</sup> Genomes for Life-GCAT lab. Germans Trias i Pujol Research Institute (IGTP), Badalona, Spain

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## **ABSTRACT**

**Objective:** Consistent physical activity is key for health and well-being, but it is vulnerable to stressors. The process of recovering from such stressors and bouncing back to the previous state of physical activity can be referred to as resilience. Quantifying resilience is fundamental to assess and manage the impact of stressors on daily physical activity. In this tutorial, we present a method to quantify the resilience process for physical activity data. We leverage the prior operationalization of resilience as area under the curve and expand it to suit the characteristics of physical activity time series. **Methods:** As use case to illustrate the methodology, we quantified resilience in step count for eight participants following the first COVID-19 lockdown as a stressor. Steps were collected daily using wrist-worn devices. The methodology is implemented in R and all coding details are included. **Results:** For each person's step count time series we fitted multiple growth models and identified the best one using the Bayesian information criterion (BIC). Then, we used the predicted values from the selected model to identify the point in time when the participant recovered from the stressor and quantified the resulting area under the curve as a measure of resilience for step count. Further resilience features were extracted to capture the different aspects of the process. **Conclusions:** By developing a methodological guide with a step-by-step implementation in R, we aimed at fostering increased awareness about the concept of resilience for physical activity and facilitate the implementation of related research.

## INTRODUCTION

Physical inactivity is responsible for the development and progression of non-communicable diseases and for premature mortality; consequently, promoting physical activity is a top-ranked public health priority (Lee et al., 2012). There is consistent evidence suggesting that physical activity (e.g., expressed as daily step counts or minutes of moderate to vigorous physical activity) is sensitive to a multitude of adverse events including, but not limited to, pandemic outbreaks (Costello et al., 2021; Larson et al., 2021), acute diseases (McKee et al., 2019), and extreme weather events (Bernard et al., 2021; Wagner et al., 2019). Additionally, other events which are not adverse *per se* (e.g., pregnancy, relocation, medical treatments) have also been shown to have a negative impact on physical activity (Corder et al., 2020; Devoogdt et al., 2010; Engberg et al., 2012). All these events can act as stressors for physical activity, and thus may be followed by a decrease in physical activity levels. The process of recovering from such stressors and bouncing back to the previous state of physical activity can be referred to as resilience (Den Hartigh & Hill, 2022; Scheffer et al., 2018). Describing and quantifying this process in the physical activity domain is therefore crucial to improve our understanding of the impacts of various stressors on individuals, to identify factors that are associated with better or worse resilience, and to foster adaptive capacities in individuals. However, so far, no methods have been reported in the literature that clearly characterize and quantify resilience from physical activity behavior data.

Resilience is an interdisciplinary construct that has been receiving increasing attention in the last decades (**Estrada et al., 2016**). Although resilience broadly relates to the ability of a system, e.g., here a human, to maintain specific functions in the presence of a stressor (**Baggio et al., 2015**), the concept has been used in many different ways across various scientific disciplines (e.g., ecology, engineering, environmental sciences, social sciences, psychology; **Scheffer et al., 2018**). This multidisciplinary interest in resilience has led to the proliferation of different conceptualizations and definitions which has hampered advances in its theoretical understanding and investigative methods (**Bryan et al., 2019; Den Hartigh & Hill, 2022**). In a recent viewpoint, Den Hartigh and Hill (**2022**) reviewed different conceptualizations of resilience in psychology. They proposed that this concept should be defined as “the process of returning to the previous state following a stressor (i.e., bouncing-back)” (p. 4), whereby stressor is understood as any event that has a disruptive negative impact on a specific system. This definition provides good conceptual clarity as it *(i)* ensures consistency with the etymological meaning of resilience (i.e., “re” – back, “salire” – to leap/jump), *(ii)* is in line with the conceptualization adopted in material sciences and the field of complex systems where this definition and measure of resilience are consolidated, and *(iii)* distinguishes the concept of resilience from other terms that have been assimilated to it in previous research, such as thriving and adaptation (**Carver, 1998; Den Hartigh & Hill, 2022**).

Measuring resilience requires the assessment of the dynamic recovery process following the exposure to one or several stressors (e.g., **Hill et al., 2018; Scheffer et al., 2018**). To this aim,

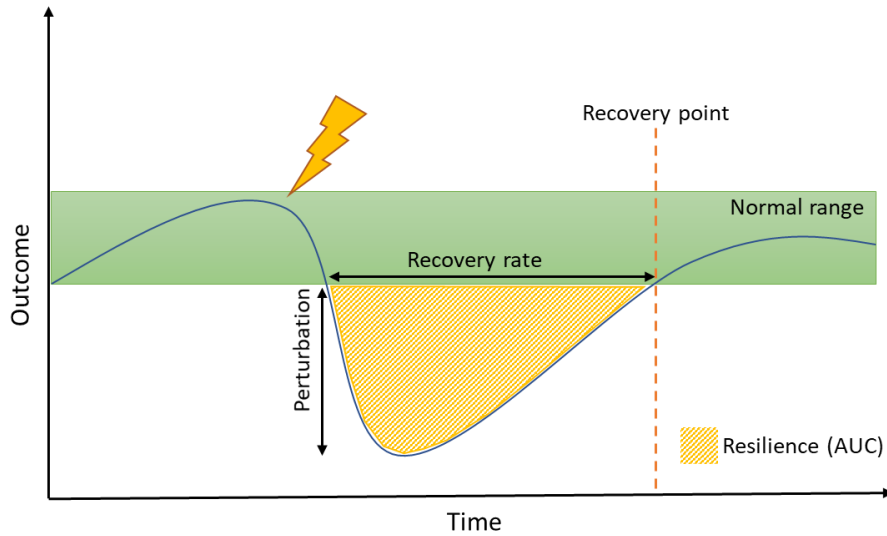
recent advances in mobile sensing have greatly facilitated the quantification of resilience by making the collection of high-resolution time series possible for various outcomes (Scheffer et al., 2018). For instance, in the physical activity domain, activity monitors or smartphones are becoming ubiquitous, facilitating the assessment of high-resolution fluctuations in physical activity in real life over prolonged periods of time (Chevance, Perski, et al., 2021). These dynamic time series measures can be leveraged to develop methods that characterize and quantify resilience (Den Hartigh & Hill, 2022; Scheffer et al., 2018). Using time series, researchers in different psychological domains (e.g., psycho-endocrinology, psycho-pathology) have adopted the area under the curve (AUC) approach to quantify resilience (Kuranova et al., 2020; Pruessner et al., 2003) (see Figure 1a). The AUC combines two independent features of the resilience process: the magnitude of the perturbation (i.e., the degree by which a specific system is impacted by a stressor) and the recovery rate (i.e., the time duration for the system to bounce back to a pre-stressor level). The trapezoid formula is commonly used to quantify the AUC from time-series and ultimately resilience (Hill et al., 2021; Pruessner et al., 2003):

$$AUC = \sum_i^{n-1} \left( \frac{(x_{i+1} + x_i) * t_i}{2} \right)$$

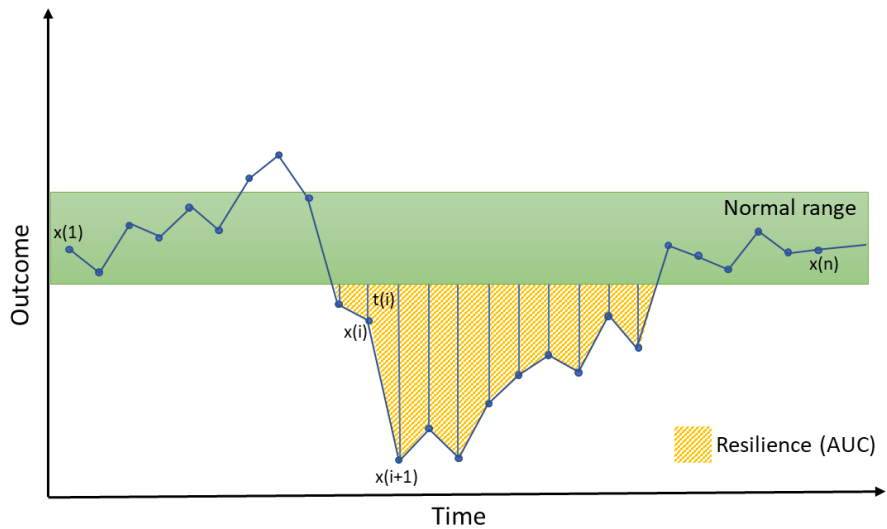
Where  $x_i$  represents the value of the variable of interest at a given time  $i$  (e.g., daily step count),  $n$  represents the total number of observations, and  $t_i$  represents the time difference between the measurement points. Figure 1b shows the AUC determined using a traditional trapezoid formula. AUC as a measure for resilience has been successfully used for outcomes

such as reaction times, experimental motor tasks or physiological signals for which resilience has previously been estimated using the trapezoid formula (e.g., Gerber et al., 2017; Hill et al., 2021). We argue here that the trapezoid formula is not suited to quantify the AUC, and ultimately the resilience process, from physical activity time series. Previous research has shown that physical activity signals (e.g., step count, minutes spent in light physical activity or moderate-to-vigorous physical activity) have the particularity of being highly variable (Chevance, Baretta, Heino, et al., 2021; Costello et al., 2021; Hooker et al., 2020) compared to the aforementioned outcomes. Therefore, identifying the recovery point and hence determining the end of the resilience process (i.e., timepoint when the system reaches relatively stable levels following its return to pre-stressor levels) based on physical activity signals is not straightforward and prone to errors. Figure 2 illustrates this “fluctuation issue” by showing two step count time series following a stressor (the time series are taken from the sample later used in the methods and results sections of this tutorial). The green horizontal line represents the pre-stressor level of daily steps while the dark grey rectangle zooms in on the part of the time series where the system has probably bounced back to the pre-stressor level; however, it is not possible to precisely identify the moment in time when this happened because of the natural fluctuations characteristic of physical activity behavior, here step count. This represents a major issue because without the identification of the recovery point it is impossible to determine the boundaries of the AUC, and thus the end of the resilience process.

Figure 1. 1a. Conceptual visualization of the resilience process as described in and adapted from Den Hartigh & Hill, 2022.

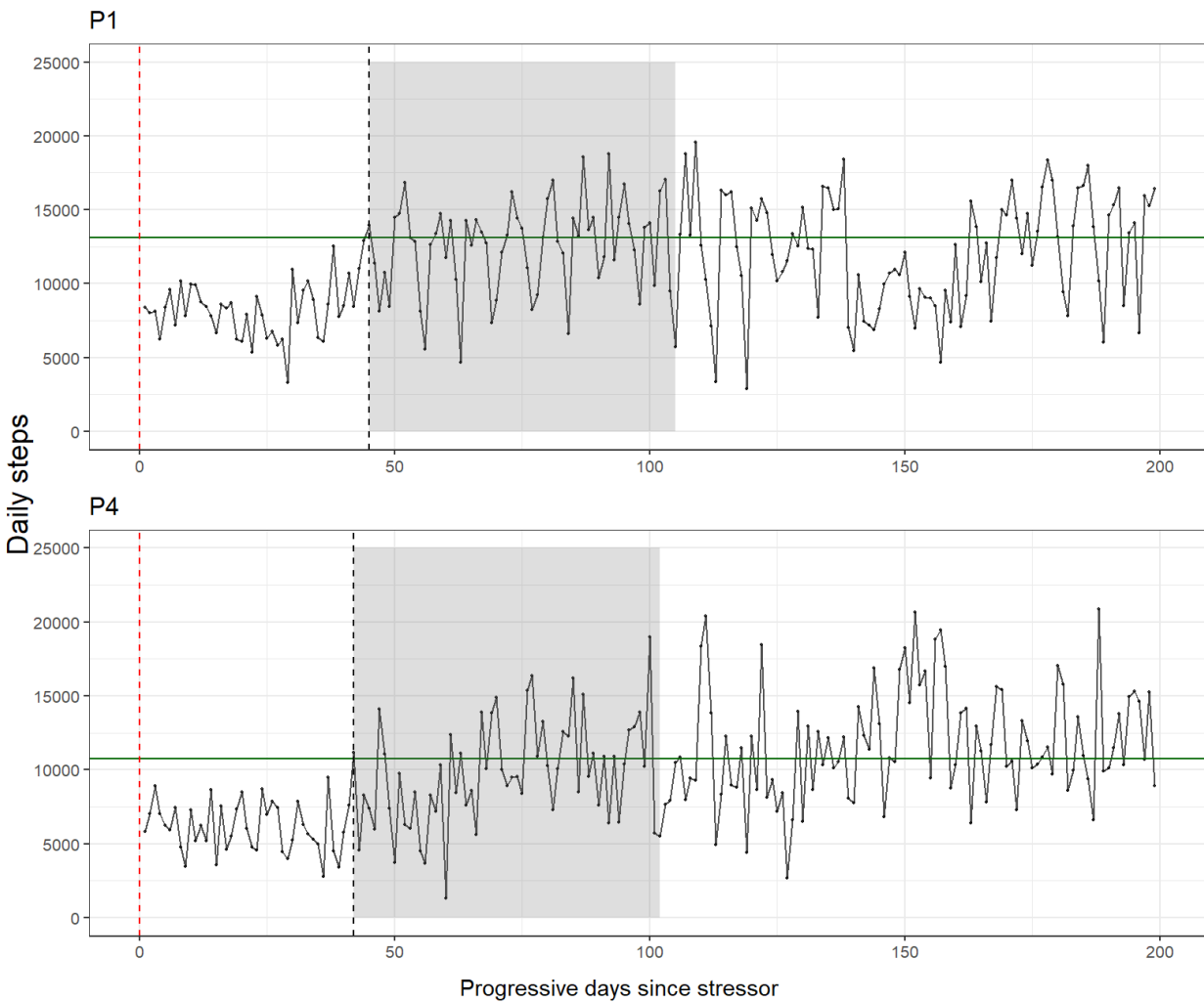


1b. Visualization of a theoretical AUC calculated using the trapezoid formula.



*Note.* Time course of time-series with several measurements; each trapezoid (in orange) is calculated using the trapezoid formula and the sum of all the trapezoids composes the area under the curve (AUC).  $x(i)$  denotes the single measurement, and  $t(i)$  denotes the time interval between the measurements. The figure is not based on real data.

Figure 2. Example of step count time series from two participants included in this tutorial.



Note. P = participant, vertical red dashed line = stressor event, horizontal green line = baseline level, black line = time series for step count, vertical black dashed line = first day after the stressor when the fluctuation in daily step count is above baseline level, grey rectangle = area highlighting intense and repeated fluctuations around baseline level: it covers 60 days following the first fluctuation above the baseline level.



## **Aim of the tutorial**

The objective of this tutorial is to introduce a new methodological approach to quantify resilience from physical activity data while accounting for the high variability and natural fluctuations of physical activity signals. Specifically, we propose to use fitted values – as opposed to observed values – to precisely identify the recovery point and therefore quantify the AUC as a measure of resilience. To this aim, we fit different growth models to each participant's time series and select the model that best describes the data. The fitted values from the selected model are then used to compute a resilience score and other indicators of the resilience process. As a use case to illustrate the application of the method, we investigate the resilience process in daily step count following the first COVID-19 lockdown (i.e., here our stressor) in Catalunya, Spain. To facilitate the application of this new method in the future, the following section details a step-by-step tutorial describing how to replicate and implement the analyses with the open-source statistical software R (R Core Team, 2021). Data and code are provided in the supplemental materials for replication (see: <https://osf.io/3h7em/>).

## **METHOD**

### **Background of the time series used in the tutorial**

To illustrate the concrete application of the proposed methodological approach, we use step count time series collected in Catalunya (Spain), as part of the COVICAT study (Kogevinas et al., 2021), in the period between October 1, 2019 and September 30, 2020. The COVICAT study

obtained ethical approval. These data were retrospectively collected using crowdsourcing from participants of the GCAT cohort (**Obón-Santacana et al., 2018**), i.e., participants consented to share their data collected via wearable devices with the research team in September 2021 with a data extraction API supported by Thryve (<https://thryve.health/>).

The resulting time series can be conceptually split into two phases by the stressor event. In this example, the stressor is represented by the start of the first COVID-19 lockdown (March 15, 2020), including a 7-week long law-enforced home confinement, which has been previously shown to have negatively impacted daily step count and other physical activity outcomes (e.g., moderate to vigorous physical activity; **Costello et al., 2021; Larson et al., 2021**). We refer to the pre-stressor phase as “baseline” and use it to compute the baseline level of daily step count. In the current example, the baseline phase corresponds to the period between October 1, 2019 and March 15, 2020. We limited the baseline phase to this period because it represents a good compromise between length of the time series and its proximity to the onset of the stressor. For the post-stressor phase, we limited the period to September 30, 2020, shortly before the second COVID-19 state of emergency was issued in Catalunya on October 15, 2020. We removed the first 2 weeks of October 2020 from the analysis because the daily step count in the time series started decreasing again with the increase in the pandemic trajectory in Catalunya. To simplify the description of the use case, we analyzed the time series for eight participants. The sample size was kept small to ensure an agile tutorial while the participants were purposely selected to showcase relevant individual differences in the resilience process.

Note that the time series used in this tutorial might contain missing values in daily step count as we did not to apply any missing value imputation. This approach is consistent with a previous viewpoint on handling missing values in longitudinal studies (Oud & Voelkle, 2014) suggesting that a time series can be seen as a way to measure an underlying process (here resilience) that develops continuously over time, even if the process is only observed at some available measurement points. For this approach, it is crucial to have enough measurement points in each time series. As a rule of thumb, we only included time series with <10% missing values in the post-stressor phase.

## Software Packages

R is a free software environment for statistical computing which provides powerful resources (i.e., packages) for data wrangling, data visualization, and a wide range of statistical modelling approaches (R Core Team, 2021). Most of the packages used in the tutorial (e.g., *dplyr*, *tidyr*, *purrr*, *ggplot*) are from the *tidyverse* ecosystem (Wickham et al., 2019). Additionally, we used functions from the *mgcv* package (Wood, 2011) for fitting non-linear models. Throughout the tutorial, we refer to a function by specifying the source package as part of the code (i.e., *package::function()*). In case the package is not mentioned, it means that the function is directly available in R without the import of any specific package. Eventually, further ad-hoc functions have been developed for the purpose of this tutorial.

The reading of the article is supported by chunks of R code embedded in the body text. Additionally, the extended R code, the time series data, and a comprehensive R Markdown file are included in the supplemental materials (<https://osf.io/3h7em/>).

## **Results**

This results section is organized into two sequential parts. The data import and pre-processing part describes how to: import the data in R (step 1), define dates relevant for quantifying the resilience process (step 2), and calculate the pre-stressor level, henceforth referred to as baseline level (step 3). The subsequent data modelling and resilience score calculation part provides guidance on how to fit growth models to the step count time series (step 4) and select the model that provides the best fit (step 5), and finally, on the use of the fitted values from the best model to calculate resilience scores and a series of other resilience features (step 6 and step 7).

### **Data import and pre-processing**

#### **Step 1: Import the data**

The participants' data are saved in a csv file named `ts_tutorial.csv` (see supplemental material). The file contains three columns named "id", "date" and "steps". The variable "id" is a string that identifies each participant, the variable "date" refers to the specific date of the measurement, and the variable "steps" corresponds to the daily number of steps done on a

specific date by a given participant. The file contains 8 time series (one time series corresponds to one participant) with 366 data points each.

In order to import the csv file in R, we use the `readr::read_csv()` function and assign it to an object:

```
df.1 <- read_csv('data_res.csv')
```

Now, the data are a data frame “df.1” with named columns and ready for data processing and modeling.

## Step 2: Define dates and phases in the time series

In the current example, we define the dates of start and end of the time series, and the date of the stressor (i.e., beginning of the lockdown). To this aim, the function `lubridate::date()` converts a string into a date format object.

```
start_ts <- lubridate::date('2019-10-01')
lckd <- lubridate::date('2020-03-15')
end_ts <- lubridate::date('2020-09-30')
```

Because we are interested in comparing the period before and after the stressor occurred, we create a new categorical variable called “phase” which specifies whether the observation is pre-lockdown (value = “baseline”) or post lock-down (value = “post-stressor”). We combine the `dplyr::mutate()` function, which allows to add variables to a data frame, with the `dplyr::case_when()` function, which is used to recode values from a variable *x* into different values in a variable *y*. The pipe symbol `%>%` is part of the **magrittr** package and allows to concatenate multiple functions in a sequential order.

```
df.2 <- df.1 %>%
  mutate(phase = case_when(date <= lckd ~ 'baseline',
                           date > lckd ~ 'post_stressor'))
```

### Step 3: Define the baseline level of daily steps and filter out the pre-stressor observations

As mentioned, the concept of resilience refers to the dynamic process of returning to a previous state. Therefore, the concept of *previous state* needs to be operationalized. We operationalized it as the lower bound of the two-sided confidence interval (95%) of the median number of daily steps during the baseline phase, which is here represented by the five months and a half preceding the lockdown. We opted for the **lower bound of the confidence interval** instead of the median itself because we wanted to identify a baseline range for step count rather than a strict threshold. We used the median instead of the mean because it is less impacted by extreme observations (i.e., outliers) or potential skewed distributions. To implement this step, we first use the `dplyr::filter()` function to include only the observations in the time series referring to the baseline phase; the `dplyr::group_by()`, `tidyr::nest()` and `purrr::map()` functions are then used to apply the `DescTools::MedianCI()` function to each participant separately. This last function calculates the median value as well as its lower and upper bounds for each time series. The argument `na.rm = TRUE` inside the `DescTools::MedianCI()` function removes the missing observations before calculating the median value while the `purrr::pluck()` function extracts the lower bound of the confidence interval from the output of `MedianCI()`.

```
baseline_level <- df.2 %>%
  filter(phase == 'baseline') %>%
  group_by(id) %>% nest() %>%
  mutate(baseline_steps = map_dbl(data,
```

```

~ DescTools::MedianCI(.$steps, conf.level =
0.95, na.rm = TRUE) %>% pluck('lwr.ci')) %>%
select(id, baseline_steps)

```

Once the baseline step count value for each participant has been defined, this information needs to be appended to a data frame which contains the part of the time series concerning the post-stressor phase only. To do so, we take the source data frame **df.2** and use **dplyr::filter()** to filter only the observations corresponding to the post-stressor phase. Then, the **baseline\_steps** variable is appended to **df.2** by joining the **baseline\_level** data frame using the **dplyr::left\_join()** function with the “id” variable as identifier. The newly created data frame **df.3** contains daily step count data for the post-stressor phase only which is the phase we analyze to measure the resilience process for each participant. Eventually, we create a new variable “prog\_day” which defines for each participant the progressive day of the time series during the post-stressor phase. This variable will then be used as predictor of daily step count in modeling the resilience process (see step 4).

```

df.3 <- df.2 %>%
  filter(phase == 'post_stressor') %>%
  left_join(baseline_level, by = 'id') %>%
  group_by(id, baseline_steps) %>%
  mutate(prog_day = seq_along(date))

```

## Data modelling and resilience score calculation

### Step 4: Applying concurrent growth models to the step count time series

Growth modeling is an analytic approach for modeling systematic within-person change across a series of repeated measurements (Grimm & Ram, 2009). The aim of a growth model is to look

at the change of a variable over time. By specifying a growth model, it is possible to precisely determine the moment in time when the participant has bounced back to the previous state (i.e., the baseline level). Different growth models can be applied to the data with the aim to see which model better fits the data and describes the change over time. In the present tutorial, we fit different types of growth models for each participant's time series: *i*) a simple linear model, also known as first-order polynomial or monomial; *ii*) a second-order polynomial to fit quadratic trends which describe non-linear patterns of change (**Blozis & Cudeck, 1999; Ram & Grimm, 2007**); and *iii*) two generalized additive models (GAMs) which allow to fit smoothed functions as combinations of multiple low-level functions (e.g., linear function, quadratic function, logarithmic function). GAMs have been introduced in order to overcome the limitations of polynomials. For instance, polynomials tend to have problems with curves that have many bends (e.g., sinusoidal patterns; **Winter & Wieling, 2016**). Accounting for such trends is particularly relevant for step count time series, which have been shown to be characterized by multiple, sudden changes over time (**Chevance, Baretta, Heino, et al., 2021**). A further reason for modelling with GAM is the opportunity to detect potential multiple drops in the step count time series. This is crucial if we think about a case where a participant has successfully recovered from the COVID-19 lock down stressor, but then a further drop in step count occurs due to another stressor (e.g., birth of a child). The growth models are specified as follows. The simple linear model (`lm_mon`) is fitted using the `lm()` function with step count (`steps`) as dependent variable and progressive day since the stressor (`prog_day`) as predictor. Note that the tilde symbol `~` in the models' formula separates the



dependent variable from the independent variable(s) and should be read as “is predicted by”.

The second-order polynomial (`lm_pol`) is an extension of the simple linear model and is fitted by adding a quadratic term  $I(\text{prog\_day}^2)$  to the linear model formula. GAMs are fitted using the `mgcv::gam()` function. Two different GAMs are fitted: `gam_tp` and `gam_cc`. The `s()` function is used within GAM model formulae to specify the smooth term through the `bs` argument (which indicates the smoothing basis to use) and the basis dimension through the `k` argument (which sets the upper limit on the degrees of freedom associated with the smooth term). In our implementation, the `bs` term specification differentiates `gam_tp` and `gam_cc`. Specifically, for the `gam_tp` model, we opted for `bs = "tp"` (i.e., thin plate regression splines) which is the default option because thin plate regression splines generally yield the best performance in terms of mean squared error (Winter & Wieling, 2016). However, we also included a GAM with `bs = "cc"` (i.e., cyclic cubic regression splines) based on previous research which used GAMs to model step count time series (Chevance, Baretta, Golaszewski, et al., 2021) and better describes cyclic trends which are common in step count data (e.g., Chevance, Baretta, Heino, et al., 2021). The `k` argument was set to `k = 7` in line with previous work on step count (Chevance et al., 2022). The preferred smoothness selection criterion we opted for is the restricted maximum likelihood (`method = 'REML'`) because it is less prone to local minima than the other criteria. The present description of the GAMs specification is based on Wood (2017) which provides a detailed description of the GAM approach and its implementation in R via the `mgcv` package.

We adopted the `tidyr::nest()` function and evoke the `purrr::map()` function to fit the different models to each person's time series separately in an idiographic fashion.

```
df.4 <- df.3 %>%
  group_by(id, baseline_steps) %>%
  nest() %>%
  mutate(lm_mon = map(data, ~ lm(steps ~ prog_day, data = .)),
         lm_pol = map(data, ~ lm(steps ~ prog_day + I(prog_day^2), data = .),
         gam_tp = map(data, ~ gam(steps ~ s(prog_day, bs = "tp", k = 7), meth
od = 'REML', data = .)),
         gam_cc = map(data, ~ gam(steps ~ s(prog_day, bs = "cc", k = 7), meth
od = 'REML', data = .)))
```

### Step 5: Selecting the best growth model for each participant

After having fitted different functions, the next step is to select the model that best describes the data for each participant individually. This step is done individually rather than at group level, because the aim is to obtain individual resilience measures. We based the model selection on the Schwarz Bayesian information criterion (BIC) as a comparative goodness-of-fit index, where lower values are associated with a better goodness-of-fit. The BIC was preferred over the Akaike's information criterion (AIC) because it suites the goal of selecting the 'correct' model with better goodness-of-fit while the AIC is a good approach if the fitted model mainly aims to predict (Chakrabarti & Ghosh, 2011). Additionally, we encourage visual inspection of each model as this contributes to selecting the best model beyond goodness-of-fit indices.

From an implementation point of view, it is necessary to compute the BIC index for all models under consideration for every participant and then select the model with the lowest index. In R, we apply the function `BIC()` to extract the BIC value from the models we computed

in the previous step. The **BIC()** function is used inside the **purrr::map\_dbl()** function because the aim is to get the values for all the time series (i.e., participants). Note that **BIC()** is part of the *flexmix* package which is automatically imported into R when the *mgcv* package is loaded. The best model (**final\_mod**) for each participant is selected by comparing the BIC values of each model (see table 1 and figure 3).

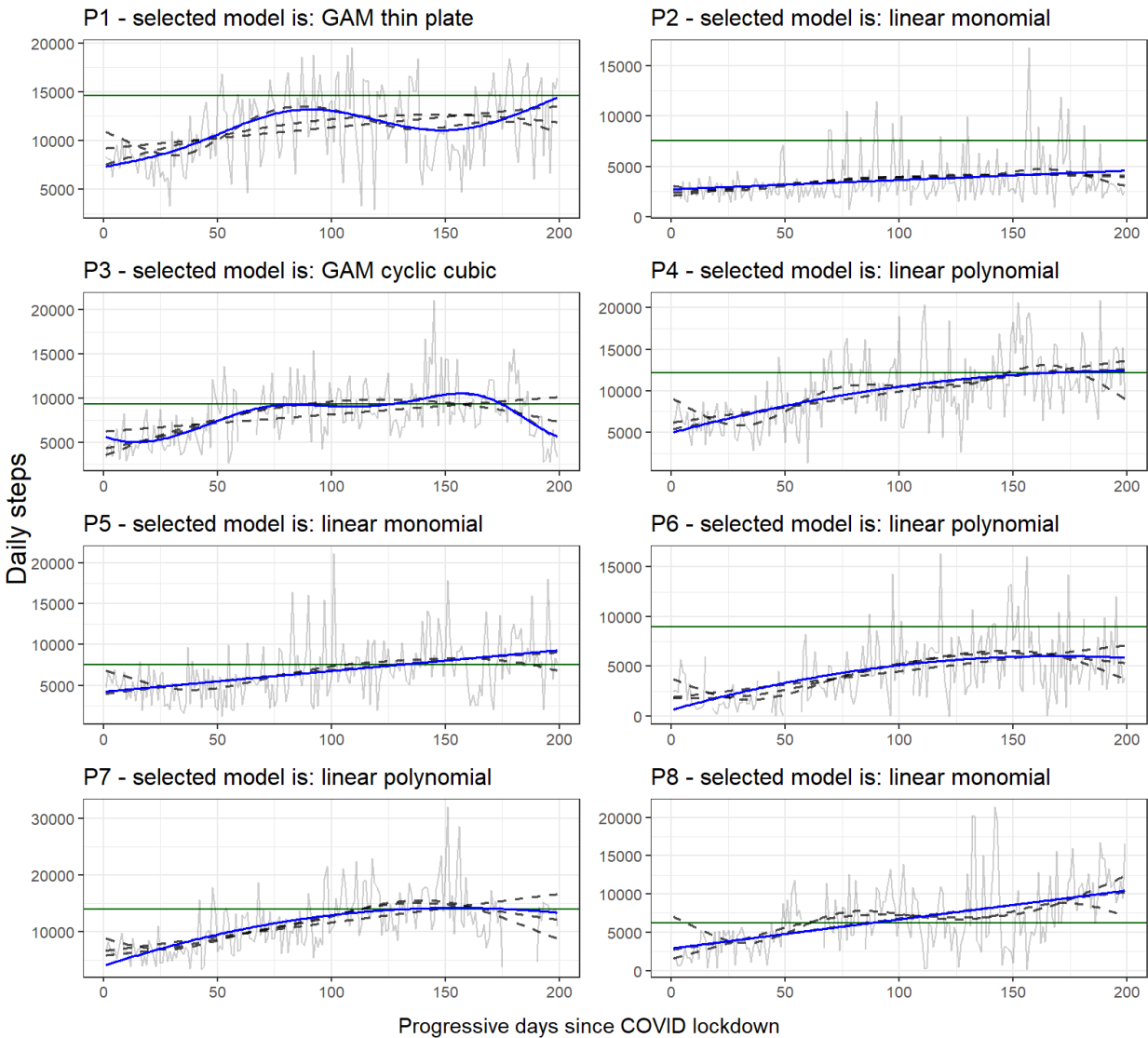
```
df.5 <- df.4 %>%
  mutate(bic_mon = map_dbl(lm_mon, BIC),
         bic_pol = map_dbl(lm_pol, BIC),
         bic_gam_tp = map_dbl(gam_tp, BIC),
         bic_gam_cc = map_dbl(gam_cc, BIC),
         final_mod = case_when(bic_mon < bic_pol & bic_mon < bic_gam_tp & bic_mon < bic_gam_cc ~ lm_mon,
                               bic_pol < bic_mon & bic_pol < bic_gam_tp & bic_pol < bic_gam_cc ~ lm_pol,
                               bic_gam_tp < bic_mon & bic_gam_tp < bic_pol & bic_gam_tp < bic_gam_cc ~ gam_tp,
                               bic_gam_cc < bic_mon & bic_gam_cc < bic_pol & bic_gam_cc < bic_gam_tp ~ gam_cc))
```

**Table 1.** Bayesian information criterion (BIC) for each model fitted to the individual time series

id	Linear monomial	Quadratic polynomial	GAM thin plate	GAM cubic cycle
P1	3820.31	3815.94	<b>3805.93</b>	3823.09
P2	<b>3660.83</b>	3662.94	3665.34	3666.43
P3	3630.28	3596.40	3597.50	<b>3595.12</b>
P4	3809.64	<b>3809.48</b>	3813.43	3821.14
P5	<b>3783.05</b>	3788.06	3783.08	3798.86
P6	3439.68	<b>3437.88</b>	3440.48	3440.08
P7	3627.13	<b>3615.84</b>	3616.75	3620.63
P8	<b>3640.32</b>	3645.44	3641.10	3682.59

Note. P = participant, in bold the BIC for the selected model

Figure 3. Comparison of growth model curves for each time series (participant)



Note. P = participant; blue line = selected model, black dashed lines = non-selected models, green horizontal green line = baseline level, grey line = observed step counts.

### Step 6: Adding the predicted values for step count to the time series

The next step is to create a new column in the time series data frame which contains the fitted values for step count from the selected model (i.e., the blue line in figure 3). We then take

the first fitted value and subtract it from baseline level in order to estimate the initial drop after the onset of the stressor. It is worth remarking the fact that we are using the first *fitted* value to identify the initial drop, therefore the result is not impacted by typical fluctuations of the *observed* values in step count time series. Within this tutorial, researchers have the option to set logical conditions to exclude participants from the analysis based on their initial drop value. For instance, participants can be excluded if they don't experience any drop after the onset of the stressor (initial drop > 0) or if the drop is not substantial. For the purpose of this tutorial, we set the logical condition of removing those participants who didn't experienced any substantial drop, defined as 20% reduction in steps relative to the baseline level (see **Chevance, Baretta, Heino, et al., 2021** for comparison of different drop thresholds in step count data). We opted for this solution because from a methodological standpoint we want to show how the proposed approach applies to the quantification of resilience for those participants who experienced a meaningful drop after the onset of the stressor. Note that the operationalization of substantial drop can be tuned by researchers to meet different research questions (e.g., relative or absolute change in step count) and fit to the study characteristics (e.g., population under scope, type of physical activity signal, type of stressor).

On the implementation side, we use the `dplyr::mutate()` function to add the fitted values (`modelr::add_predictions`) from the selected model (`final_mod`) to each time series (`data`). Then we apply the `init_drop()` function which we developed for this tutorial. The function extracts the first fitted value for each time series according to the selected model and

subtracts it from the baseline level. As next step, we define the substantial drop (**sub\_drop**) as 20% of baseline level. Eventually, if the **init\_drop** value is smaller than **sub\_drop**, we remove the participant from the subsequent analysis because it means that there was no substantial drop after the onset of the stressor.

```
df.6 <- df.5 %>%
  mutate(data = map2(data, final_mod, ~ add_predictions(.x, .y, var = "pred_steps")),
         init_drop = map2_dbl(final_mod, baseline_steps, init_drop),
         sub_drop = baseline_steps * 0.2) %>%
  filter(init_drop > sub_drop)
```

### Step 7: Quantifying and characterizing the resilience process

As a final step, we quantify resilience, operationalized as the AUC (see Figure 1), and we also provide indicators of additional resilience features (see table 2 and figure 4). A detailed descriptions of these parameters and their implementation in R is now presented while a visualization of these parameters is provided in figure 4.

1. **Initial drop.** The indicator corresponds to the difference between baseline level and the fitted value at the first day after the stressor. It quantifies the system perturbation informing whether and how much step count decreased after the onset of the stressor (expressed in steps compared to the baseline level). The function used to compute the initial drop is **init\_drop()**.
2. **Recovery Rate.** This resilience feature informs about the duration for the system to bounce back to the baseline level and thus is expressed in number of days. In order to compute it, we need to identify the recovery point (here the day) when the fitted value from the selected model is equal or greater than the baseline level. In order to do so, we apply the **rec\_rate()** function

which is an ad-hoc built function. If the `rec_rate()` returns a missing value (**NA**), it means that the individual has not recovered from the stressor during the time period considered in the time series (200 days in the current example). In this case, one option is to extend the length of the time series (post-stressor phase) and check if a longer period of time allows to identify the time point when the system recover from the stressor.

3. **Main resilience score 1: *Area Under the Curve (AUC)***. The AUC represents the total number of steps reduced between the onset of the stressor until the recovery point compared to baseline. In order to calculate it and hence quantify the resilience process, we use a formula that calculates the cumulative difference between the predicted values and the baseline values in the time period before the recovery happens:

$$AUC = \sum_i^n (|baseline - f(x_i)|)$$

Where  $n$  corresponds to the recovery rate value, *baseline* represents the baseline value, and  $f(x_i)$  is the fitted value of steps at measurement point  $i$ . The AUC value represents the cumulative decrease in steps after the onset of the stressor and is expressed in terms of number of steps. The resilience process should be then interpreted as follows: a lower AUC value describes a better resilience process while a higher AUC value describes a worse resilience process. In case the recovery rate function returns a missing value (i.e., no recovery happened), the AUC is calculated from the length of the time series instead of from the recovery rate ( $n$  argument in the AUC function). This means that the AUC for participants who do not recover from the

stressor is artificially limited and tends to be underestimated. The corresponding R function `auc()` was developed for this tutorial.

4. **Main resilience score 2: *Relative Area Under the Curve (rAUC)***. The AUC provides a measure of the resilience process in absolute terms. Though this information is of crucial importance to answer various research questions at an idiographic level (e.g., what is the impact of a stressor  $x$  on step count for the individual  $y$ ), it does not allow to make adequate comparisons between individuals unless the baseline level is taken into account. As an example, let us consider two individuals ( $y$ ,  $z$ ) with the same recovery rate (100 days) and same AUC (100'000 total steps), but with different baseline levels (e.g., 5'000 for individual  $y$ , 8'000 for individual  $z$ ). It follows that in relative terms, the stressor  $x$  has impacted the individual  $y$  more than the individual  $z$ . To account for it, we propose a function `rel_auc()` to calculate a further parameter that weights the resilience score based on the baseline level and is calculated as the AUC divided by the baseline level. This value represents the relative impact produced by the stressor as a ratio of the baseline level for each individual.

$$rAUC = \left( \frac{AUC}{baseline * n} \right)$$

Where  $AUC$  represents the area under the curve,  $n$  corresponds to the recovery rate value or the length of the time series in case the individual hasn't recovered from the stressor, and  $baseline$  represents the baseline value.



5. *Maximum perturbation*. The maximum perturbation corresponds to the difference between baseline and the smallest fitted value during the resilience process and it is expressed in steps. The function used to compute the initial drop is `max_drop()`. Note that depending to the selected model (e.g., linear, GAM), the *maximum perturbation* may overlap to the *initial drop* in most of the cases.
6. *Day of maximum perturbation*. It corresponds to the day of the time series when the maximum drop occurred. The function used to compute the initial drop is `max_drop()`.
7. *Average perturbation*. This resilience descriptor refers to the daily average impact of the stressor on step count data (steps per day). We develop the ad-hoc function `avg_prtb()` to extract this parameter.

$$\text{Average Perturbation} = \left( \frac{AUC}{n} \right)$$

Where *AUC* represents the area under the curve and *n* corresponds to the recovery rate value or the length of the time series in case the individual hasn't recovered from the stressor. This is relevant for understanding the average daily decrease in steps following the onset of the stressor.

Finally, the function `res_plot()` returns a ggplot object that shows the resilience process (see figure 5).

```
length_ts <- as.integer(end_ts - lckd)
df.7 <- df.6 %>%
  mutate(recovery_rate = map2_dbl(baseline_steps, data, ~ rec_rate(.x, .y$pred_steps)),
```

```

    resilience = pmap_dbl(list(baseline_steps, data, recovery_rate), ~ auc(..1, ..2$pred_steps, ..3)),
    rel_resilience = pmap_dbl(list(resilience, baseline_steps, length_ts, recovery_rate), ~ rel_auc(..1, ..2, ..3, ..4)),
    max_pert = map2_dbl(final_mod, baseline_steps, ~ max_drop(.x, .y)),
    max_pert_day = map2_dbl(final_mod, baseline_steps, ~ which_drop(.x, .y)),
    avg_perturbation = pmap_dbl(list(resilience, recovery_rate, length_ts), ~ avg_prtb(..1, ..2, ..3)),
    res_plot = pmap(list(data, baseline_steps, recovery_rate, id), ~ res_plot(..1, ..2, ..3, ..4, ymax = 25000))

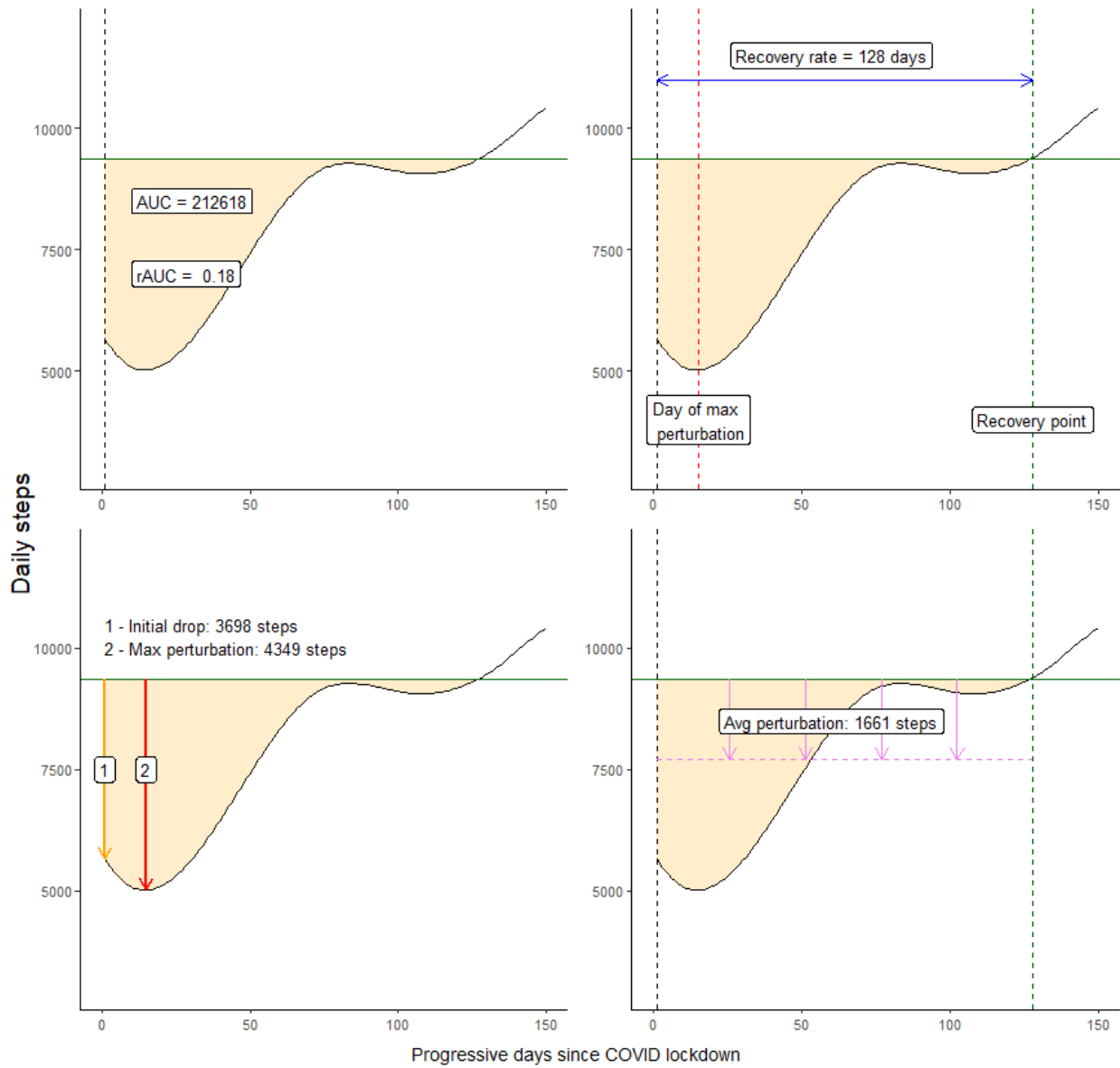
```

Table 2. Comparison of resilience scores and resilience features across participants

id	Baseline level <sup>1</sup>	Initial drop <sup>2</sup>	Recovery rate <sup>3</sup>	AUC <sup>1</sup>	rAUC <sup>4</sup>	Max pert <sup>1</sup>	Max pert day <sup>5</sup>	Avg pert <sup>1</sup>
P1	14589	7245	NA	640886	0.22	7245	1	3204
P2	7528	4784	NA	768963	0.51	4784	1	3844
P3	9370	3698	128	212618	0.18	4349	15	1661
P4	12143	7136	164	450445	0.23	7136	1	2746
P5	7569	3299	131	216025	0.22	3299	1	1649
P6	8956	8280	NA	886527	0.49	8280	1	4432
P7	14061	9978	134	499632	0.27	9978	1	3728
P8	6236	3301	89	145392	0.26	3301	1	1633
<b>Mean</b>	10057	5965	129	477561	0.30	6047	3	2862

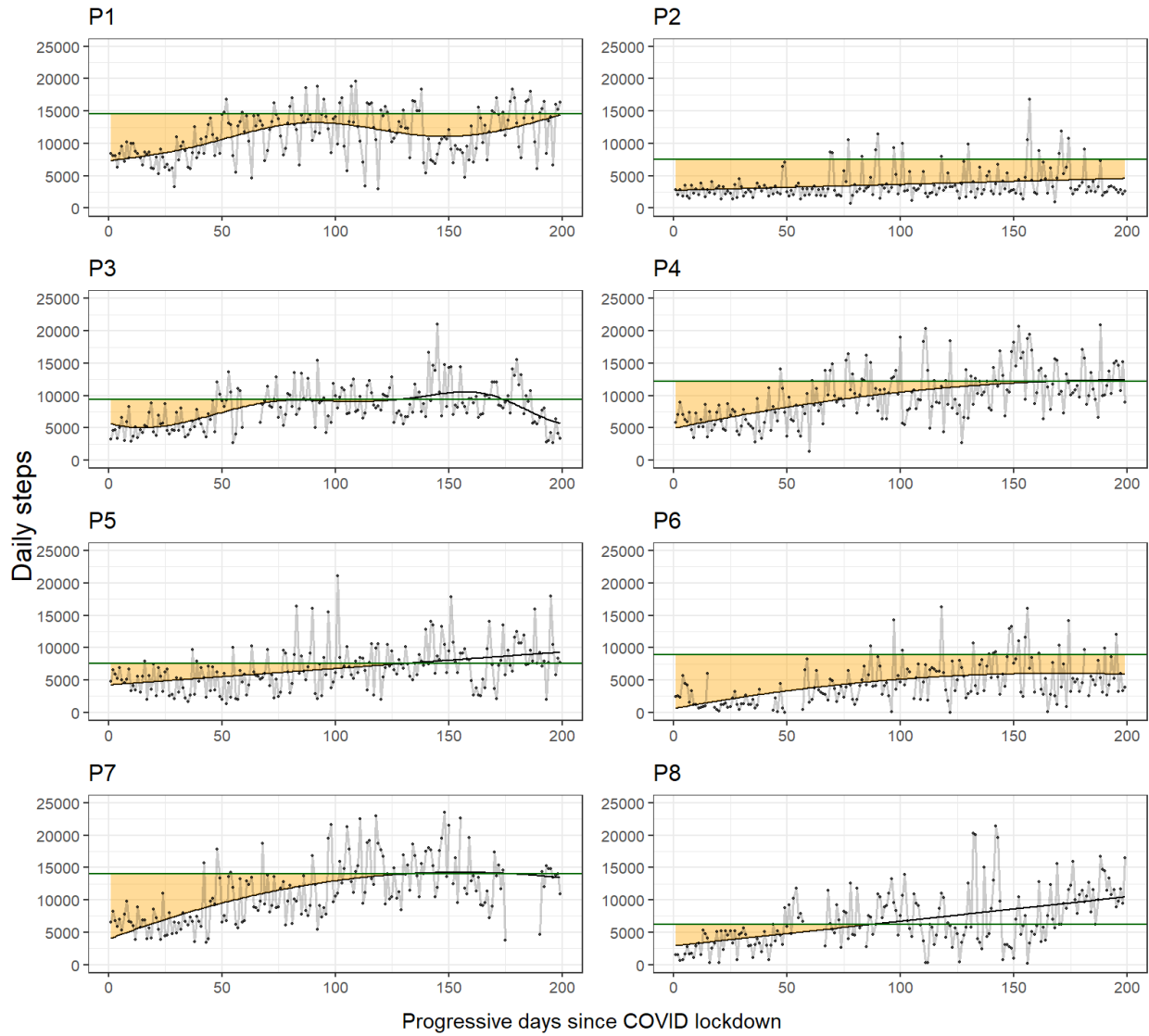
Note. Units for resilience scores and features are: <sup>1</sup> = steps, <sup>2</sup> = delta steps, <sup>3</sup> = number of days, <sup>4</sup> = percentage, <sup>5</sup> = progressive day since stressor; pert = perturbation; NA = baseline level not recovered during the study

Figure 4. Visualization of resilience scores and features for participant P3



Note. Green horizontal line = baseline level of steps, AUC = area under the curve, rAUC = relative area under the curve, avg = average.

Figure 5. Visualization of resilience process for each time series (participant)



Note. P = participant; orange area = resilience; green horizontal line = baseline steps; plain black line = fitted step count values; grey line = observed values for step count.

## **Discussion**

We conclude this tutorial with an illustrative overview of the interpretation of results coming from the implementation of the proposed methodological approach and a discussion on the advantages, its limitations, and some research implications.

### **Results interpretation**

The provided resilience scores and features allow to explore whether participants managed to return to their pre-lockdown level of step count, when it happened, and how much their daily step count decreased after the onset of the stressor (see table 2). For instance, five out of eight participants recovered after the onset of the stressor (average recovery time of 129 days) while three participants did not recover during the post-stressor phase (200 days following the stressor). Seven out of eight experienced the maximum perturbation right after the lockdown (day of maximum perturbation = 1) with an initial average drop of 6,249 daily steps after which their trajectory improved. Only one participant (P3) experienced the maximum drop 15 days after the onset of the stressor. On average, the resilience score of the eight participants is of 477,561 steps, while the average perturbation is of 2,862 steps per day during the recovery process. This last number is in line with previous research (Costello et al., 2021) showing an average decrease of 2,872 steps per day following the COVID-19 pandemic mitigation strategies in San Diego, California. Furthermore, thanks to the main resilience scores (AUC), we are able to estimate the overall decrease of step count following the onset of the COVID-19 lockdown. From an idiographic standpoint, we can see that participants who never bounced back to pre-

lockdown level of step count (P1, P2, P6) share the worst resilience scores (640,886, 768,963 and 886,527 steps respectively) and, on average, they 'lost' 3,204, 3,844 and 4,432 steps per day during the 200 days following the lockdown. Finally, from a more qualitative point of view, it is possible to see that the resilience trajectory of five out of eight participants is represented by non-linear growth models (GAM with thin plate smooth term for P1; GAM with cyclic cubic smooth term for P3; quadratic model for P4, P6, P7) while the resilience trajectory of the other three participants is better characterized with linear models (see figures 3 and 5). Overall, results suggested that the resilience process might differ extensively across individuals both quantitatively and qualitatively.

### **Strengths and limitations**

The innovative aspect of the approach presented in this tutorial is that it leverages the fitted values from the selected growth model to quantify the AUC and ultimately resilience using an idiographic approach. By using the fitted values, the method allows to control for the natural daily fluctuations in step count data and, hence, identify the point in time when the individual recovers from the stressor. Additionally, by fitting growth models, the proposed approach is consistent with the conceptualization of resilience as a *process* (Den Hartigh & Hill, 2022; Scheffer et al., 2018). In the tutorial, we used this method to quantify resilience from step count data as a use case, but its application is not limited to this physical activity outcome. It can be used also to explore the resilience process for other physical activity outcomes which are characterized by

high variability (e.g., minutes spent in light or moderate to vigorous physical activity; **Costello et al., 2021; Hooker et al., 2020**). Additionally, further health-related signals characterized by high variability, e.g., psychotherapy outcomes (**Olthof et al., 2020**) or heart rate variability (**Namazi, 2021**), might benefit from this methodology. Another strength of this tutorial includes the utilization of the open-source statistical software R, which should facilitate the replication and application of the proposed method. This aspect is particularly relevant as R is becoming increasingly popular among researchers from the social sciences working with time series (e.g., **Stadnitski & Wild, 2019**).

The current tutorial is not without limitations. First, we proposed a methodological approach that suites relatively long time series and it might not be appropriate to assess resilience in case where the number of measurement points doesn't allow to model the data properly (i.e., measurement points <50; **Stadnitski & Wild, 2019**). Additionally, since the proposed method aims to control for natural fluctuations in physical activity behavior, it would not allow to assess resilience in case the recovery rate is so fast that it can be confused with the typical time series fluctuations (e.g., a 3 days recovery rate for step count after the formation of a blister on a foot). A further limitation is that this tutorial included just one type of stressor: future applications of this approach to assess the impact of other stressors on step count and other physical activity signals will help to consolidate the methodology (**Liu et al., 2022**). Last, we presented four types of growth models to fit the step count data. For the sake of conciseness, we did not expand on growth model tuning and instead proposed to fit functions that have been shown to be appropriate to model step count data in the past (**Chevance, Baretta, Golaszewski, et**

al., 2021; Chevance et al., 2022). However, it would be possible to define further functions (e.g., polynomial cubic, GAMs with different types and number of dimensions) for inclusion in the growth model comparison (as part of step 4 and 5).

## **Research implications**

This tutorial provides a methodological toolbox that can foster and facilitate further scientific investigation in different ways. First, it allows to explore the determinants of the resilience process (e.g., psychological factors, individual differences, environmental barriers and facilitators) for physical activity. Understanding how individual differences, such as physiological, psychological or contextual factors, may lead to different resilience outcome is crucial to identify intervention strategies that improve individuals' adaptive capacities and ultimately promote faster and smoother resilience. Additionally, the provided resilience scores can be used to assess and compare the efficacy of specific interventions to promote efficient recovery in physical activity following a stressor. For instance, the AUC and the other resilience indicators (e.g., recovery rate, average perturbation) can be used as outcomes to test the effectiveness of interventions aiming at reducing the impact of stressors on physical activity.

## **Conclusions**

In this tutorial article, we presented a new methodological approach to quantify and characterize resilience for physical activity data and provided support for its implementation with the open-source software R. We sought to generate a methodological guide with a step-by-step



implementation that would contribute to create a ready-to-go toolbox that can be easily applied by interested readers. Ultimately, we hope this tutorial article fosters increased awareness about the concept of resilience for physical activity time series, and stimulates interest in further studying this process.

## **Contributions**

Conceptualization: DB, GC, SK; Data curation: DB, SK, IC, AC, GCV, JGA, RdC, AC; Funding acquisition: RdC, GCV, JGA, GC, SK; Investigation: DB, GC, SK, IC; Methodology: DB; Software: DB; Writing – original draft: DB; Writing – review & editing: all the authors.

## **Conflicts of interest.**

The authors have no competing interests to declare that are relevant to the content of this article.

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## **Data and Supplementary Material Accessibility**

The data and materials (datasets, R code, R Markdown file) for all analyses are available at <https://osf.io/3h7em/>.

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