



Contents lists available at ScienceDirect

## Psychology of Sport &amp; Exercise

journal homepage: [www.elsevier.com/locate/psychsport](http://www.elsevier.com/locate/psychsport)

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

Dario Baretta<sup>a,\*</sup>, Sarah Koch<sup>b,c,d</sup>, Inés Cobo<sup>b,c,d</sup>, Gemma Castaño-Vinyals<sup>b,c,d</sup>, Rafael de Cid<sup>e</sup>, Anna Carreras<sup>e</sup>, Joren Buekers<sup>b,c,d</sup>, Judith Garcia-Aymerich<sup>b,c,d</sup>, Jennifer Inauen<sup>a</sup>, Guillaume Chevance<sup>b,c,d</sup>

<sup>a</sup> Institute of Psychology, University of Bern, Fabrikstrasse 8, 3012, Bern, Switzerland

<sup>b</sup> Barcelona Institute for Global Health (ISGlobal), C/ Doctor Aiguader, 88, 08003, Barcelona, Spain

<sup>c</sup> Universitat Pompeu Fabra (UPF), Plaça de la Mercè, 10-12, 08002, Barcelona, Spain

<sup>d</sup> CIBER de Epidemiología y Salud Pública (CIBERESP), C/ Monforte de Lemos 3-5, 28029, Madrid, Spain

<sup>e</sup> Genomes for Life-GCAT Lab, Germans Trias i Pujol Research Institute (IGTP), Camí de Les Escoles s/n, 08916, Badalona, Barcelona, Spain

## ARTICLE INFO

## Keywords:

Resilience  
Physical activity  
Time series  
R tutorial  
AUC  
Wearable devices

## ABSTRACT

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 consistent physical activity. In this tutorial, we present a method to quantify the resilience process from physical activity data. We leverage the prior operationalization of resilience, as used in various psychological domains, as area under the curve and expand it to suit the characteristics of physical activity time series. As use case to illustrate the methodology, we quantified resilience in step count time series (length = 366 observations) for eight participants following the first COVID-19 lockdown as a stressor. Steps were assessed daily using wrist-worn devices. The methodology is implemented in R and all coding details are included. For each person's time series, we fitted multiple growth models and identified the best one using the Root Mean Squared Error (RMSE). 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. By developing a methodological guide with a step-by-step implementation, we aimed at fostering increased awareness about the concept of resilience for physical activity and facilitate the implementation of related research.

## 1. 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, Bader-Larsen, & Magkos, 2021), acute diseases (McKee et al., 2019), and extreme weather events (Bernard et al., 2021; Wagner, Keusch, Yan, & Clarke, 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

\* Corresponding author. Institute of Psychology, Department of Health Psychology and Behavioral Medicine, University of Bern, Fabrikstrasse 8, 3012, Bern, Switzerland.

E-mail address: [dario.baretta@unibe.ch](mailto:dario.baretta@unibe.ch) (D. Baretta).

<https://doi.org/10.1016/j.psychsport.2022.102361>

Received 15 June 2022; Received in revised form 25 October 2022; Accepted 5 December 2022

Available online 8 December 2022

1469-0292/© 2022 The Authors. Published by Elsevier Ltd. This is an open access article under the CC BY license (<http://creativecommons.org/licenses/by/4.0/>).

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, Severt, & Jiménez-Rodríguez, 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, Brown, & Hellebrandt, 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). The 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 (Den Hartigh & Hill, 2022; Fletcher & Sarkar, 2013; Windle, 2011). This issue is evident in research on resilience in psychology, where a major argument of debate concerns the conceptualization of resilience as either a trait or a process (Fletcher & Sarkar, 2013; Luthar, Cicchetti, & Becker, 2000; Windle, 2011). Resilience as a *trait* has been referred to as a set of personal qualities that enable a person to adapt and thrive in the face of the circumstances and adversities they encounter (Block & Block, 1982; Connor & Davidson, 2003). Traits like general resourcefulness, strength of character, and flexibility of functioning in response to various environmental demands are considered descriptors of resilience as a trait (Fletcher & Sarkar, 2013). This notion has been criticized because it suggests that resilience is a quality (i.e., trait) that one either has or does not have and does not represent the dynamics of a process that changes over time and across contexts (Den Hartigh & Hill, 2022; Fletcher & Sarkar, 2013; Luthar et al., 2000). Resilience as a *process* can be reconducted to various conceptualizations that we can sort into three broad categories (Bryan, O'Shea, & MacIntyre, 2019; Den Hartigh & Hill, 2022; Smith et al., 2008). The first category refers to resilience as an ability to resist stressors and maintain a healthy state in spite of stressors (Bonanno, 2004; Bryan et al., 2019; Luthar et al., 2000). In the second category, resilience is conceptualized as the ability to adapt to and grow from stressors, and, ultimately, improve the level of functioning (Richardson, 2002). A third conceptualization, supported by various researchers across different scientific fields (Carver, 1998; Den Hartigh & Hill, 2022; Scheffer et al., 2018), refers to resilience as the process of returning to the previous state following a stressor (“bouncing-back”; Den Hartigh & Hill, 2022, p. 4), whereby stressor is understood as any event that has a disruptive negative impact on a specific system (e.g., physical activity). 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 physical sciences, ecology, biology, engineering 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). The conceptualization of resilience as a process – and specifically as a bouncing back process – is commonly used in the sport psychology context, whereby resilience acts as a dynamic state subject to both change over time and context (Bryan et al., 2019; Hill, Den Hartigh, Meijer, De Jonge, & Van Yperen, 2018). In the remainder of the tutorial, we will refer to resilience adopting this latter conceptualization.

Measuring the resilience process requires the assessment of the dynamic recovery following the exposure to one or several stressors (Hill et al., 2018; Scheffer et al., 2018). Therefore, multiple measurement points (i.e., time series) need to be collected in order to capture how a person's state responds to, and bounces back from, stressors. Methodological approaches to quantify resilience from time series have been proposed and implemented in the last years (Den Hartigh & Hill, 2022; Helmich et al., 2021; Kuranova et al., 2020; Scheffer et al., 2018). 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, & Hekler, 2021). These dynamic time series measures allow to capture the person's state along the stressor-recovery process and 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 from time series (Kuranova et al., 2020; Pruessner, Kirschbaum, Meinschmid, & Hellhammer, 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).

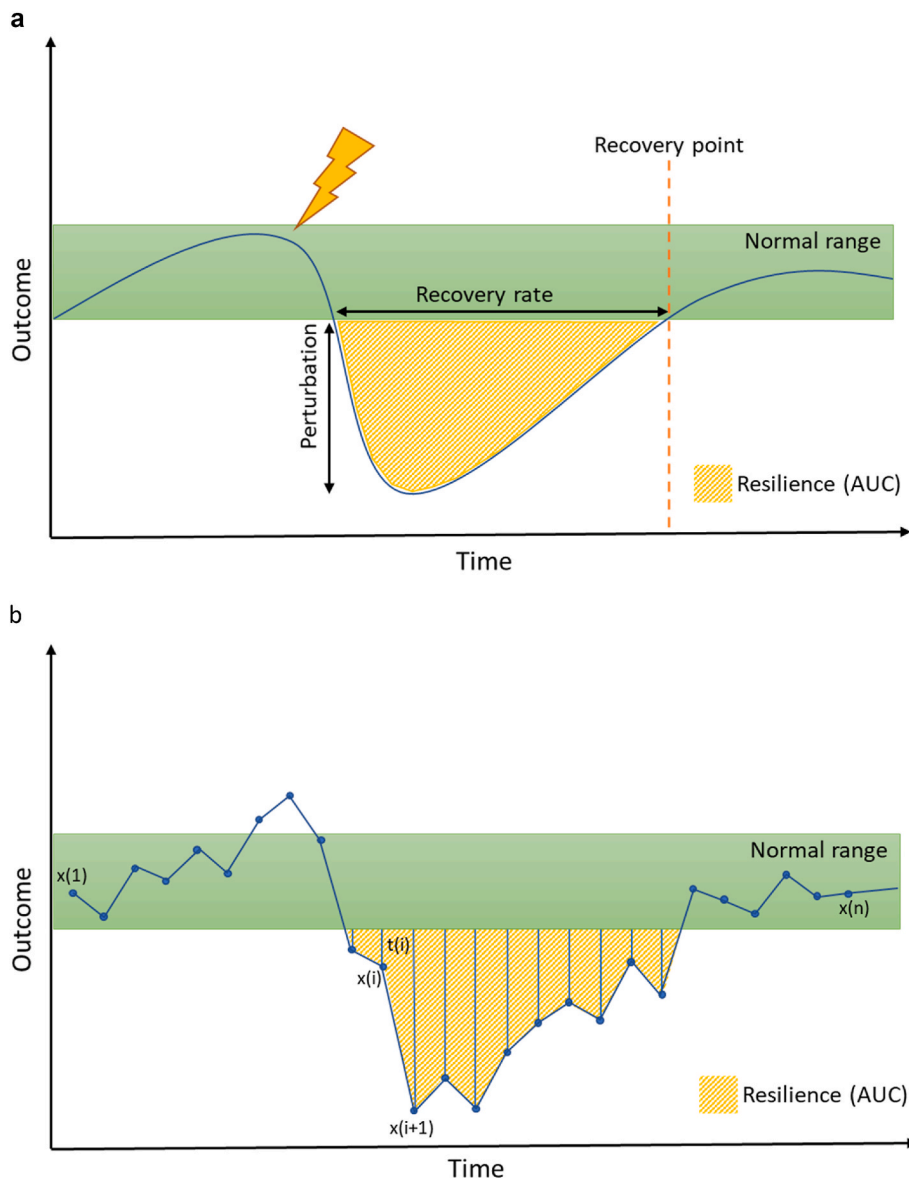
The trapezoid formula is commonly used to quantify the AUC from time-series and ultimately resilience (Hill, Van Yperen, & Den Hartigh, 2021; Pruessner et al., 2003):

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

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. Based on this operationalization of resilience, the larger the AUC the less resilient is the person to recover from the stressor. 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 compared to the aforementioned outcomes (Chevance, Baretta, Heino, et al., 2021; Costello et al., 2021; Hooker, Oswald, Reid, & Baron, 2020). 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.

### 1.1. 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



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

model are then used to compute a resilience score and other indicators of the resilience process for each individual. Modeling time series for each individual separately allow us to quantify the process of resilience for each study participant, as if we were using a traditional questionnaire to measure any other psychological construct at the individual level. This approach ensures that every type of research can then be conducted using idiographic or group-based designs and statistics.

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 available in an Open Science Framework directory (see: <https://osf.io/3h7em/>).

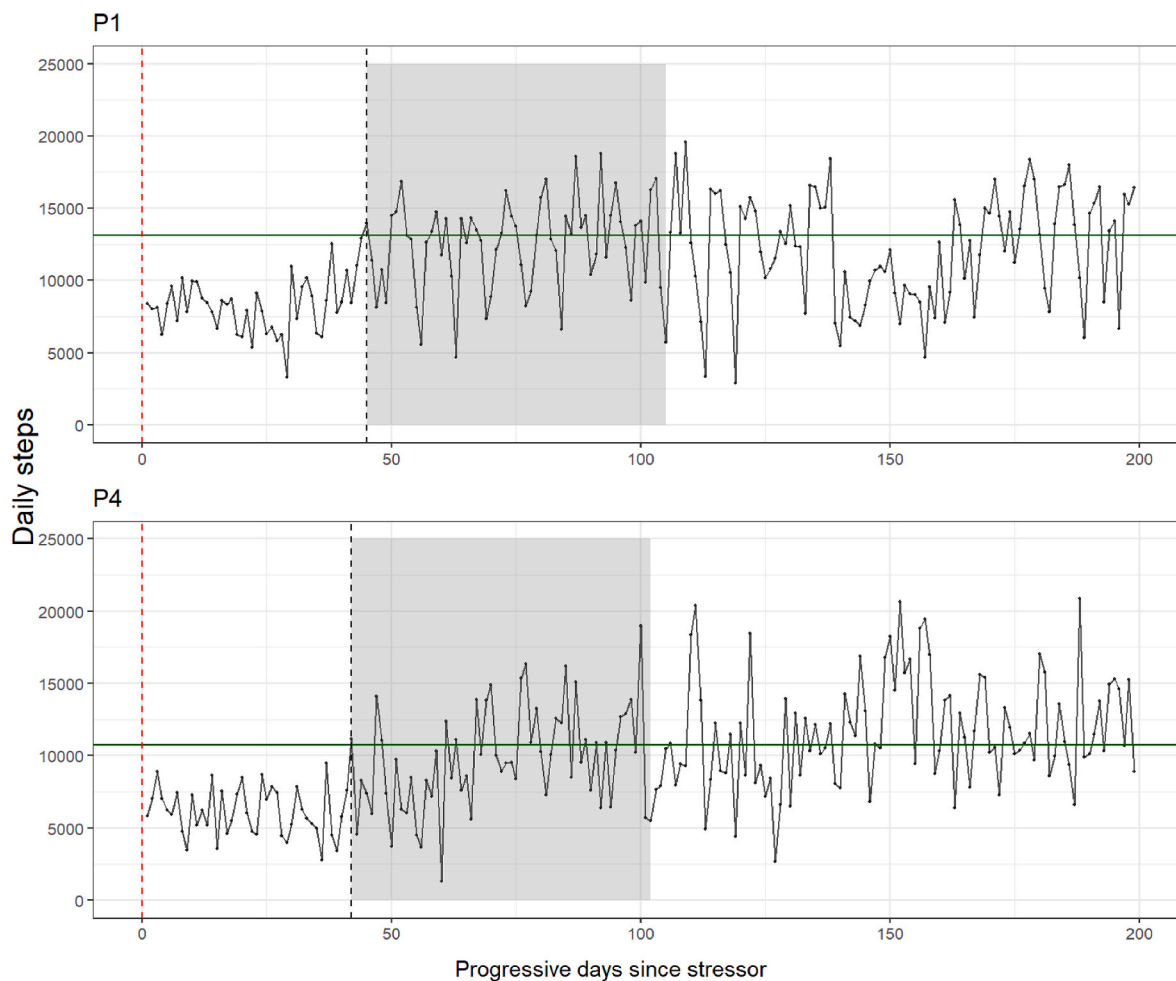
## 2. Methods

### 2.1. 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. 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,



**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.

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.

The time series used in this tutorial might contain missing values in daily step count as we did not 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.

Note that there are other use cases where the date of the stressor is unknown or varies idiosyncratically; therefore, defining the date of the system perturbation can be more problematic. In such situations, we suggest to adopt data-driven methods that have been shown to effectively detect abrupt or structural changes in physical activity time series such as recursive portioning or break point detection methods

(Chevance, Baretta, Heino, et al., 2021; Costello et al., 2021).

## 2.2. 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/>).

## 3. 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

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

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

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

(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).

### 3.1. Data import and pre-processing

#### 3.1.1. 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:

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

#### 3.1.2. 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.

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.

#### 3.1.3. 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()`.

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).

### 3.2. Data modelling and resilience score calculation

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

Growth modeling is an analytic approach for modeling systematic within-person ce 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). Two different GAMs are fitted using the `mgcv::gam()`: `gam_tp` and `gam_cc`. The `s()` function is used within the 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)

```
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)
```

```
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))
```

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, Baretta, Romain, Godino, & Bernard, 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.

### 3.2.2. 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 (i.e., a score for each potential participant). We based the model selection on the Root Mean Squared Error (RMSE) which tells how close the model's fitted values are to the observed data points (Hyndman & Koehler, 2006). The RMSE is an absolute and direct measure of model fit (i.e., it is expressed in the same units as the dependent variable) where the best fitting model has an ideal value of zero. When used comparatively, lower RMSE values are associated with a better model fit.<sup>1</sup> Therefore, by comparing RMSEs between different models we can select the one that minimizes the average mean squared errors (i.e., residuals), which are here represented by daily fluctuations in the time series. For instance, looking at the RMSE values for participant P1 (Table 1), we can see that the estimates from "GAM thin plate" are more accurate than the ones from "GAM cubic cycle" by 155 steps per day. Differently, other participants present smaller differences in RMSE values between models, making the comparison and the relevant choice between the two models more challenging (e.g., less than 10 steps per day; see P4, P5, P6). In such cases, we recommend to combine the RMSE with a further model fit

index which is less sensitive to outliers: the mean absolute error (MAE; Chai & Draxler, 2014). This index can be interpreted in the same way as the RMSE (i.e., an absolute index with smaller values indicating a better fit) with the difference that it penalizes the outliers less (see Chai & Draxler, 2014 for a comparison between RMSE and MAE). If both RMSE and MAE values provide support for the same model, we can consider it as the one that better describes the data. Otherwise, in case of discrepancies (e.g., P5 and P6 in Table 1), we encourage visual inspection of each model as this contributes to selecting the best model beyond fit indices. Eventually, if there are still concerns regarding the model selection, it is possible to run some sensitivity analyses to check if the two models lead to substantial differences in the resilience process. This approach is presented in the supplemental materials. Now, for sake of conciseness, we continue the tutorial focusing on the model selection based on the RMSE index.

From an implementation point of view, it is necessary to compute the RMSE for all models under consideration for every participant and then

**Table 1**

Root mean squared error (RMSE) and mean absolute error (MAE) for each model fitted to the individual time series.

Participant	RMSE			MAE		
	GAM TP	GAM CC	diff	GAM TP	GAM CC	diff
P1	<b>3139</b>	3294	-155	<b>2476</b>	2683	-207
P2	2278	<b>2231</b>	46	1568	<b>1524</b>	44
P3	<b>2554</b>	2573	-19	<b>2030</b>	2045	-15
P4	3281	<b>3277</b>	4	2586	<b>2563</b>	22
P5*	<b>3122</b>	3131	-9	2298	<b>2293</b>	5
P6*	<b>2823</b>	2832	-9	2121	<b>2106</b>	15
P7	<b>3894</b>	3951	-57	<b>2976</b>	3104	-128
P8	<b>3552</b>	3963	-411	<b>2637</b>	3080	-443

*Note.* In bold the RMSE for the selected model; RMSE and MAE values as well as differences in RMSE and MAE are expressed as number of steps; negative values in RMSE and MAE difference corresponds to a better performance for GAM thin plate; \* = RMSE and MAE values are not consistently pointing to the same model.

```
df.4 <- df.3 %>%
  group_by(id, baseline_steps) %>%
  nest() %>%
  mutate(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 = .)))
```

select the model with the lowest value. In R, we apply the function `modelr:rmse()` to extract the RMSE value from the models we computed in the previous step. The `modelr:rmse()` 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). The best model (`final_mod`) for each participant is selected by comparing the RMSE values of each model (see Table 1 and figure 3). In case the reader wants to extract the MAE values as a further model's fit index, the function to be used is `modelr:mae()`.

### 3.2.3. 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. Conversely, estimating the initial drop on the basis of the first observed value would probably lead to under- or over-estimating the size of the drop and not be representative of the time series trajectory

(see figure 2). 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()`

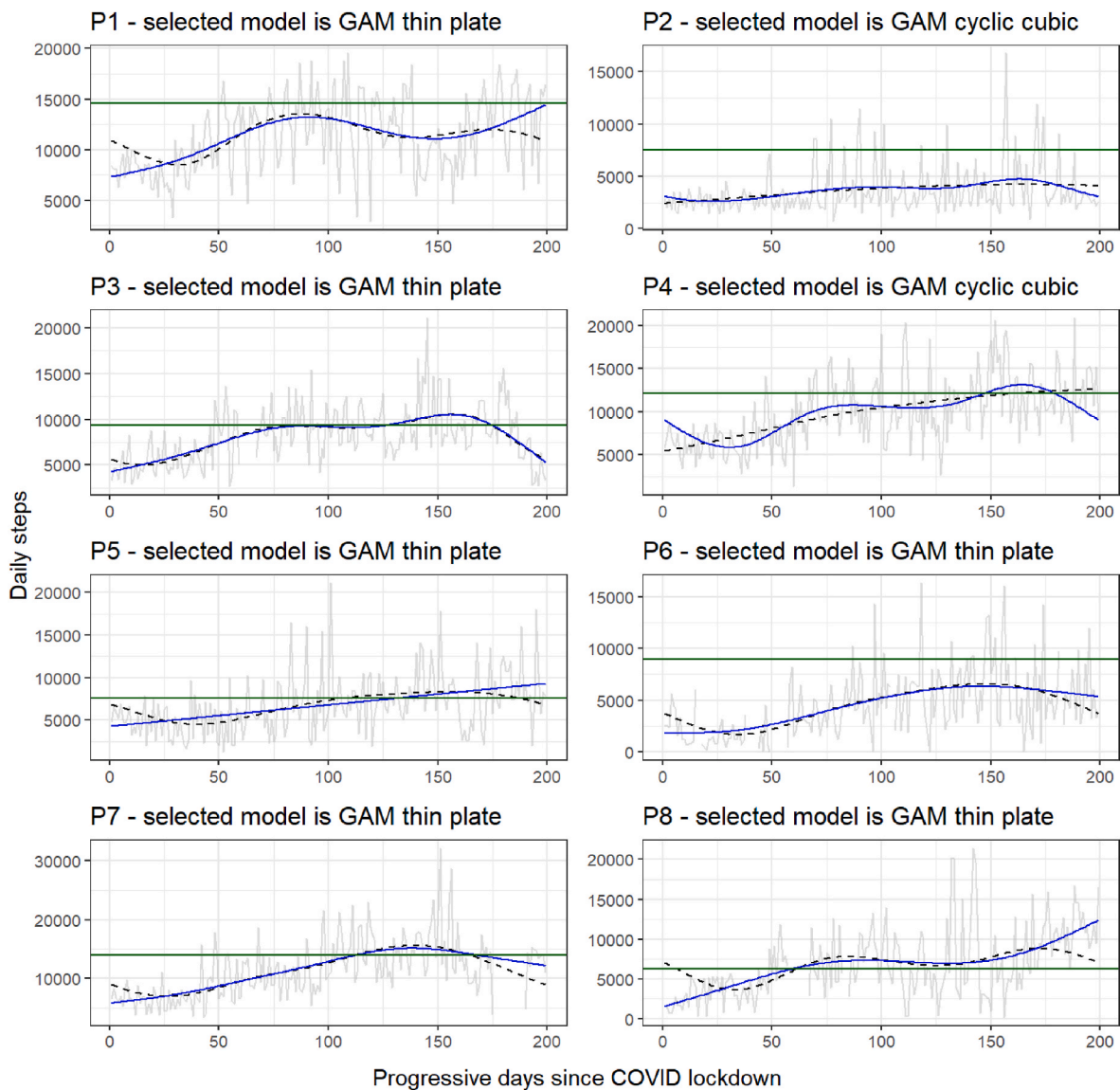


Figure 3. Comparison of growth model curves for each time series (participant).

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

```
df.5 <- df.4 %>%
  mutate(rmse_gam_tp = map2_dbl(gam_tp, data, ~ modelr::rmse(.x, .y)),
         rmse_gam_cc = map2_dbl(gam_cc, data, ~ modelr::rmse(.x, .y)),
         mae_gam_tp = map2_dbl(gam_tp, data, ~ modelr::mae(.x, .y)),
         mae_gam_cc = map2_dbl(gam_cc, data, ~ modelr::mae(.x, .y)),
         final_mod = case_when(rmse_gam_tp < rmse_gam_cc ~ gam_tp,
                               rmse_gam_cc < rmse_gam_tp ~ gam_cc))
```

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.

### 3.2.4. 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. Similar to what done in step 6 with the initial drop parameter, the recovery rate can be used as a further criterion to define whether a perturbation has to be considered significant or not. Participants can be then excluded from subsequent analyses if the perturbation they experienced lasted less than a specific amount of time. Also in this case, the threshold for the exclusion can be defined by researchers according to their different research questions and study characteristics. In this tutorial, we didn't specify any exclusion criteria based on the length of the recovery rate.

**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: the lower the AUC value the higher the resilience and the higher the AUC value the lower the resilience. 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 (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. Here again, the lower the relative AUC value the higher the resilience and the higher the relative AUC value the lower the resilience. Relative AUC values are bounded between 0 and 1 and can be interpreted as a percentage "lost" during the resilience process and compared to the baseline value.

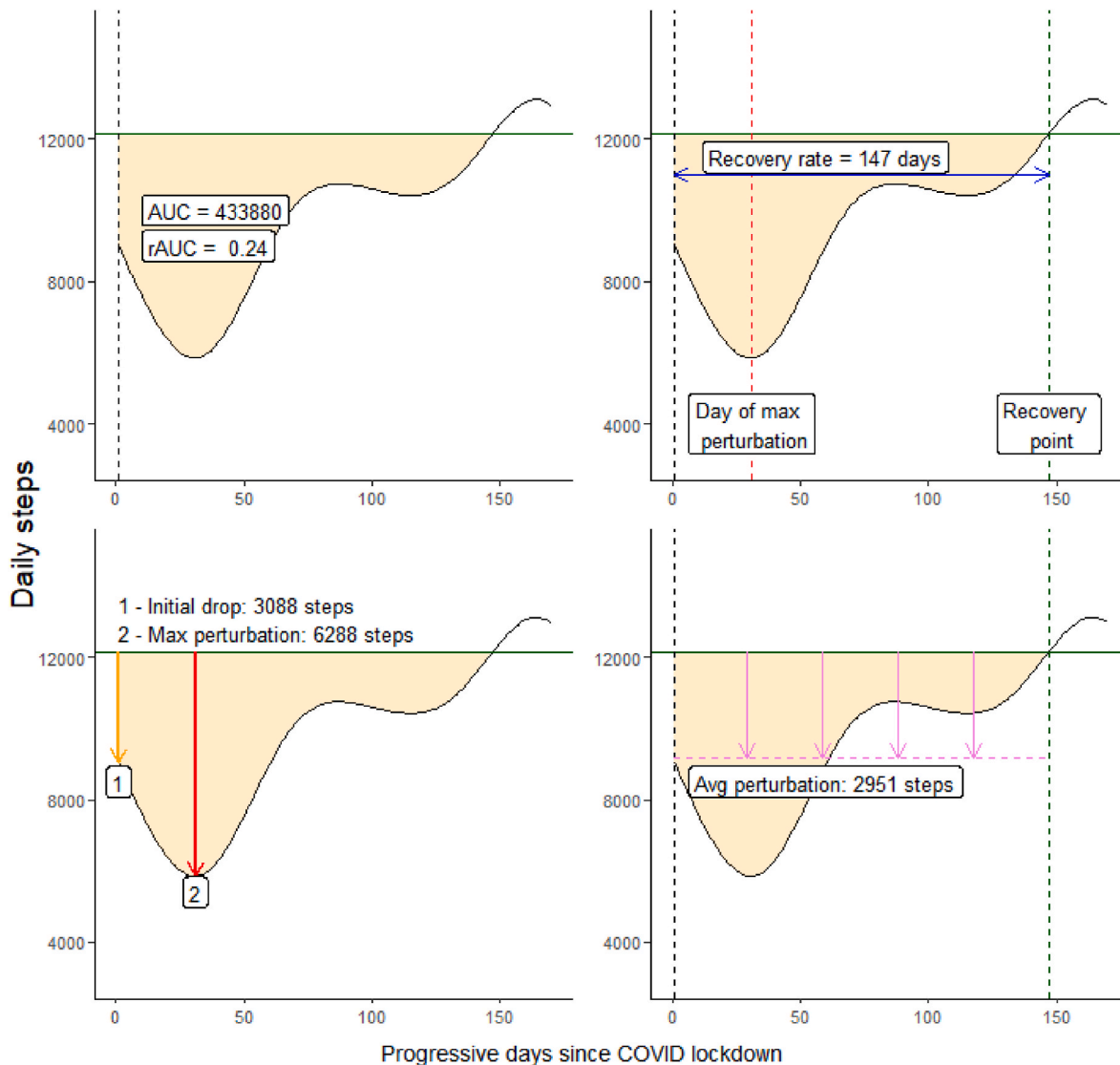
```
df.6 <- df.5 %>%
  mutate(data = map2(data, final_mod, ~ add_predictions(.x, .y, var = "pred_steps")),
         init_drop = map2_dbl(final_mod, baseline_steps, init_drop),
         sub_drop = baseline_steps * 0.2) %>%
  filter(init_drop > sub_drop)
```



**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	3220
P2	7528	4432	NA	768962	0.51	4912	23	3864
P3	9370	5060	127	215773	0.18	5060	1	1699
P4	12143	3088	147	433880	0.24	6288	31	2951
P5	7569	3300	131	216012	0.22	3300	1	1648
P6	8956	7111	NA	893954	0.50	7125	12	4492
P7	14061	8231	114	517333	0.32	8231	1	4538
P8	6236	4651	59	133942	0.36	4651	1	2270
<b>Mean</b>	10057	5390	116	477593	0.32	5852	9	3085

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. Mean values for recovery rate have been calculated after removing NAs.



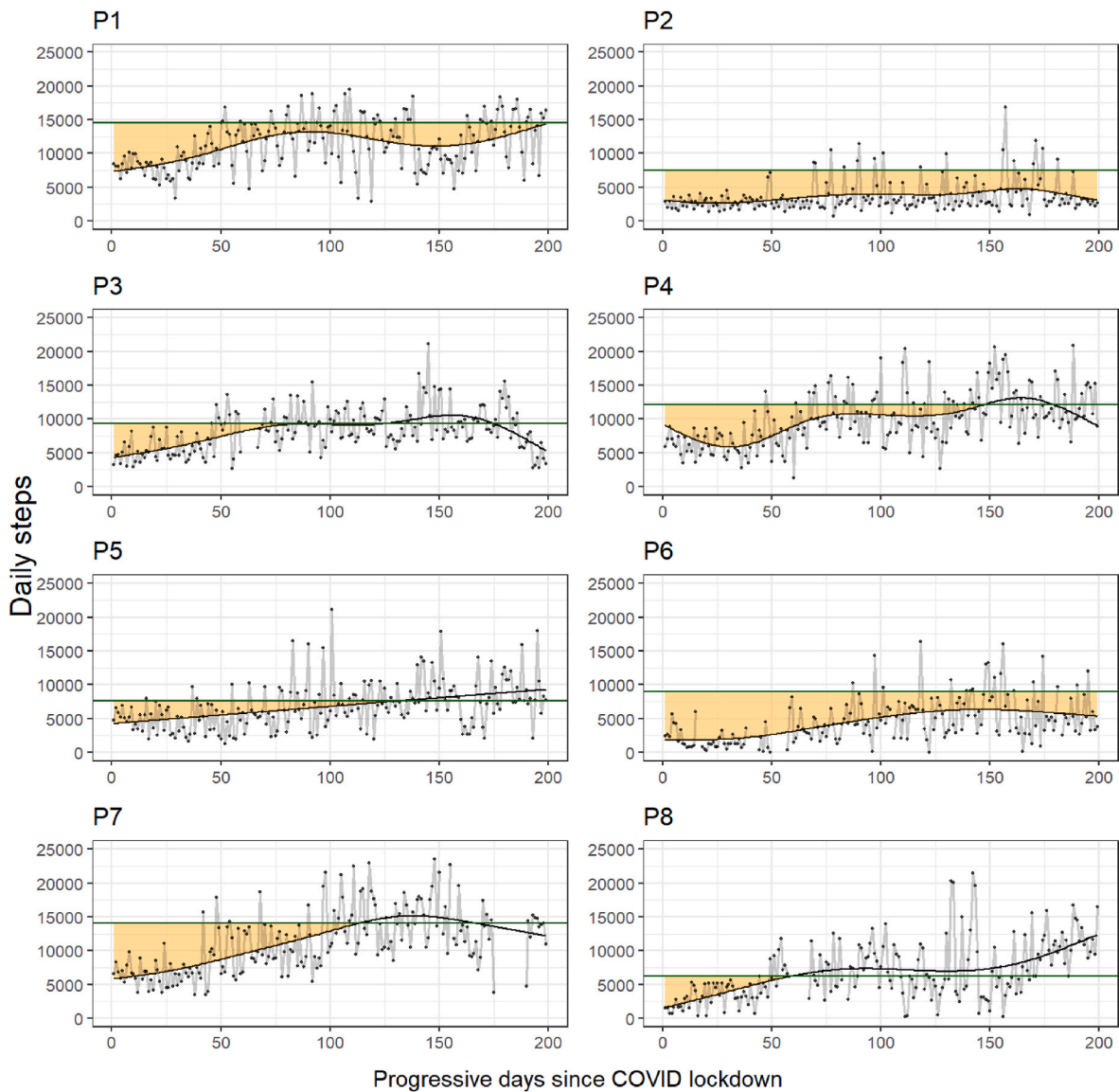
**Figure 4.** Visualization of resilience scores and features for participant P4.

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

**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.



**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.

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

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](#)).

<sup>1</sup> In line with the aim of this tutorial, the RMSE was preferred over the Akaike's information criterion (AIC) and the Bayesian information criterion (BIC) because we are not interested in explaining or predicting the step count time series using a parsimonious model. Instead, the focus of this methodological approach is to extract the trend from the time series and remove the fluctuation issue typical of physical activity signals.

#### 4. 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.

##### 4.1. 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 116 days) while three participants did not recover during the post-stressor phase (200 days following the stressor). Five out of eight experienced the maximum perturbation right after the lockdown (day of maximum perturbation = 1) with an initial average drop of 5,697 daily

```
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)))
```

steps after which their trajectory improved. Three participants (P2, P4, P6) experienced the maximum drop between 12 and 31 days after the onset of the stressor. On average, the resilience score of the eight participants is of 477,593 steps, while the average perturbation is of 3,085 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 the pre-lockdown level of step count (P1, P2, P6) share the worst resilience scores (640,886, 768,962 and 893,954 steps respectively) and, on average, they ‘lost’ 3,220, 3,864, and 4,492 steps per day during the 200 days following the lockdown. Overall, results suggested that the resilience process might differ extensively across individuals.

#### 4.2. 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. 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 together with an open access dataset, 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 suits 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. Lastly, 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., GAMs with different types and number of dimensions) for inclusion in the growth model comparison (as part of step 4 and 5).

#### 4.3. 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, by leveraging the intensive longitudinal nature of the time series, psychological and contextual factors assessed at daily level (e.g., self-regulatory and planning skills, weather conditions, air pollution) can be used as predictors of the resilience trajectory. For this specific purpose, the resilience outcome has to be broken down at daily level, where each observation is represented by the difference between baseline and the fitted value on a given day (i.e.,  $baseline - f(x_t)$ ). Eventually, 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.

## 5. 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.

## Disclosure and acknowledgements

Supplemental materials including the extended R code, the data source, and a comprehensive R Markdown file containing code inputs and outputs are available at <https://osf.io/3h7em/>. This study makes use of data generated by the GCAT-Genomes for Life. Cohort study of the Genomes of Catalonia, Fundació IGTP and COVICAT Study Group (Cohort Covid de Catalunya). IGTP is part of the CERCA Program/Generalitat de Catalunya. GCAT was funded by Acció de Dinamització del ISCIII-MINECO and the Ministry of Health of the Generalitat de Catalunya (ADE 10/00026); and have additional support by the Agència de Gestió d'Ajuts Universitaris i de Recerca (AGAUR) (2017-SGR 529), National Grant PI18/01512 and VEIS project (001-P-001647) (co-funded by European Regional Development Fund (ERDF), "A way to build Europe"). COVICAT is supported by ISGlobal and IGTP and funded by EIT COVID-19 Rapid Response activity 20873A and SR20-01024 La Caixa Foundation. The Barcelona Institute for Global Health (ISGlobal) receives support from the Spanish Ministry of Science, Innovation and Universities through the 'Centro de Excelencia Severo Ochoa 2019–2023' Programme (CEX2018-000806-S), and support from the Generalitat de Catalunya through the CERCA Programme. The author SK and this project were supported by the European Commission through a MSCA-IF (10.3030/840513). The authors of this study would like to acknowledge all GCAT participants who collaborate to this study and all GCAT project investigators who contributed to the generation of the GCAT data. A full list of the investigators is available from [www.genomesforlife.com](http://www.genomesforlife.com).

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

The data and R code used in this tutorial are available at <https://osf.io/3h7em/>.

## Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.psychsport.2022.102361>.

## References

Baggio, J., Brown, K., & Hellebrandt, D. (2015). Boundary object or bridging concept? A citation network analysis of resilience. *Ecology and Society*, 20(2). <https://doi.org/10.5751/ES-07484-200202>

Bernard, P., Chevance, G., Kingsbury, C., Baillot, A., Romain, A.-J., Molinier, V., Gadais, T., & Dancause, K. N. (2021). Climate change, physical activity and sport: A

systematic review. *Sports Medicine*, 51(5), 1041–1059. <https://doi.org/10.1007/s40279-021-01439-4>

Block, J. H., & Block, J. (1982). The role of ego-control and ego-resiliency in the organization of behavior. In *Development of cognition, affect, and social relations*. Psychology Press.

Bonanno, G. A. (2004). Loss, trauma, and human resilience: Have we underestimated the human capacity to thrive after extremely aversive events? *American Psychologist*, 59, 20–28. <https://doi.org/10.1037/0003-066X.59.1.20>

Bryan, C., O'Shea, D., & MacIntyre, T. (2019). Stressing the relevance of resilience: A systematic review of resilience across the domains of sport and work. *International Review of Sport and Exercise Psychology*, 12(1), 70–111. <https://doi.org/10.1080/1750984X.2017.1381140>

Carver, C. S. (1998). Resilience and thriving: Issues, models, and linkages. *Journal of Social Issues*, 54(2), 245–266. <https://doi.org/10.1111/j.1540-4560.1998.tb01217.x>

Chai, T., & Draxler, R. R. (2014). Root mean square error (RMSE) or mean absolute error (MAE)? – arguments against avoiding RMSE in the literature. *Geoscientific Model Development*, 7(3), 1247–1250. <https://doi.org/10.5194/gmd-7-1247-2014>

Chevance, G., Baretta, D., Golaszewski, N., Takemoto, M., Shrestha, S., Jain, S., Rivera, D. E., Klasnja, P., & Hekler, E. (2021). Goal setting and achievement for walking: A series of N-of-1 digital interventions. *Health Psychology: Official Journal of the Division of Health Psychology, American Psychological Association*, 40(1), 30–39. <https://doi.org/10.1037/hea0001044>

Chevance, G., Baretta, D., Heino, M., Perski, O., Olthof, M., Klasnja, P., Hekler, E., & Godino, J. (2021). Characterizing and predicting person-specific, day-to-day, fluctuations in walking behavior. *PLoS One*, 16(5), Article e0251659. <https://doi.org/10.1371/journal.pone.0251659>

Chevance, G., Baretta, D., Romain, A. J., Godino, J. G., & Bernard, P. (2022). Day-to-day associations between sleep and physical activity: A set of person-specific analyses in adults with overweight and obesity. *Journal of Behavioral Medicine*, 45(1), 14–27. <https://doi.org/10.1007/s10865-021-00254-6>

Chevance, G., Perski, O., & Hekler, E. B. (2021). Innovative methods for observing and changing complex health behaviors: Four propositions. *Translational Behavioral Medicine*, 11(2), 676–685. <https://doi.org/10.1093/tbm/ibaa026>

Connor, K. M., & Davidson, J. R. T. (2003). Development of a new resilience scale: The Connor-Davidson Resilience Scale (CD-RISC). *Depression and Anxiety*, 18(2), 76–82. <https://doi.org/10.1002/da.10113>

Corder, K., Wimpenny, E. M., Foubister, C., Guagliano, J. M., Hartwig, X. M., Love, R., Clifford Astbury, C., & van Sluijs, E. M. F. (2020). Becoming a parent: A systematic review and meta-analysis of changes in bmi, diet, and physical activity. *Obesity Reviews*, 21(4), Article e12959. <https://doi.org/10.1111/obr.12959>

Costello, V. L., Chevance, G., Wing, D., Mansour-Assi, S. J., Sharp, S., Golaszewski, N. M., Young, E. A., Higgins, M., Ibarra, A., Larsen, B., & Godino, J. G. (2021). Impact of the COVID-19 pandemic on objectively measured physical activity and sedentary behavior among overweight young adults: Yearlong longitudinal analysis. *JMIR Public Health and Surveillance*, 7(11), Article e28317. <https://doi.org/10.2196/28317>

Den Hartigh, R. J. R., & Hill, Y. (2022). Conceptualizing and measuring psychological resilience: What can we learn from physics? *New Ideas in Psychology*, 66, Article 100934. <https://doi.org/10.1016/j.newideapsych.2022.100934>

Devoogdt, N., Van Kampen, M., Geraerts, I., Coremans, T., Fieuws, S., Lefevre, J., Philippaerts, R., Truijens, S., Neven, P., & Christiaens, M.-R. (2010). Physical activity levels after treatment for breast cancer: One-year follow-up. *Breast Cancer Research and Treatment*, 123(2), 417–425. <https://doi.org/10.1007/s10549-010-0997-6>

Engberg, E., Alen, M., Kukkonen-Harjula, K., Peltonen, J. E., Tikkanen, H. O., & Pekkarinen, H. (2012). Life events and change in leisure time physical activity. *Sports Medicine*, 42(5), 433–447. <https://doi.org/10.2165/11597610-000000000-00000>

Estrada, A. X., Severt, J. B., & Jiménez-Rodríguez, M. (2016). Elaborating on the conceptual underpinnings of resilience. *Industrial and Organizational Psychology*, 9(2), 497–502. <https://doi.org/10.1017/iop.2016.46>

Fletcher, D., & Sarkar, M. (2013). Psychological resilience: A review and critique of definitions, concepts, and theory. *European Psychologist*, 18(1), 12–23. <https://doi.org/10.1027/1016-9040/a000124>

Gerber, M., Ludyga, S., Mücke, M., Colledge, F., Brand, S., & Pühse, U. (2017). Low vigorous physical activity is associated with increased adrenocortical reactivity to psychosocial stress in students with high stress perceptions. *Psychoneuroendocrinology*, 80, 104–113. <https://doi.org/10.1016/j.psyneuen.2017.03.004>

Grimm, K. J., & Ram, N. (2009). Non-linear growth models in mplus and SAS. *Structural Equation Modeling: A Multidisciplinary Journal*, 16(4), 676–701. <https://doi.org/10.1080/10705510903206055>

Helmich, M. A., Olthof, M., Oldehinkel, A. J., Wichers, M., Bringmann, L. F., & Smit, A. C. (2021). Early warning signals and critical transitions in psychopathology: Challenges and recommendations. *Current Opinion in Psychology*, 41, 51–58. <https://doi.org/10.1016/j.copsyc.2021.02.008>

Hill, Y., Den Hartigh, R. J. R., Meijer, R. R., De Jonge, P., & Van Yperen, N. W. (2018). Resilience in sports from a dynamical perspective. *Sport, Exercise, and Performance Psychology*, 7(4), 333–341. <https://doi.org/10.1037/spy0000118>

Hill, Y., Van Yperen, N. W., & Den Hartigh, R. J. R. (2021). Facing repeated stressors in a motor task: Does it enhance or diminish resilience? *Journal of Motor Behavior*, 53(6), 717–726. <https://doi.org/10.1080/00222895.2020.1852155>

Hooker, S. A., Oswald, L. B., Reid, K. J., & Baron, K. G. (2020). Do physical activity, caloric intake, and sleep vary together day to day? Exploration of intraindividual variability in 3 key health behaviors. *Journal of Physical Activity and Health*, 17(1), 45–51. <https://doi.org/10.1123/jpah.2019-0207>

Hyndman, R. J., & Koehler, A. B. (2006). Another look at measures of forecast accuracy. *International Journal of Forecasting*, 22(4), 679–688. <https://doi.org/10.1016/j.ijforecast.2006.03.001>

- Kogevinas, M., Castaño-Vinyals, G., Karachaliou, M., Espinosa, A., de Cid, R., Garcia-Aymerich, J., ... Tonne, C. (2021). Ambient air pollution in relation to SARS-CoV-2 infection, antibody response, and COVID-19 disease: A cohort study in Catalonia, Spain (COVICAT study). *Environmental Health Perspectives*, 129(11), 117003. <https://doi.org/10.1289/EHP9726>
- Kuranova, A., Booi, S. H., Menne-Lothmann, C., Decoster, J., van Winkel, R., Delespaul, P., De Hert, M., Derom, C., Thiery, E., Rutten, B. P. F., Jacobs, N., van Os, J., Wigman, J. T. W., & Wichers, M. (2020). Measuring resilience prospectively as the speed of affect recovery in daily life: A complex systems perspective on mental health. *BMC Medicine*, 18(1), 36. <https://doi.org/10.1186/s12916-020-1500-9>
- Larson, E. A., Bader-Larsen, K. S., & Magkos, F. (2021). The effect of COVID-19-related lockdowns on diet and physical activity in older adults: A systematic review. *Aging and Disease*, 12(8), 1935–1947. <https://doi.org/10.14336/AD.2021.0606>
- Lee, I.-M., Shiroma, E. J., Lobelo, F., Puska, P., Blair, S. N., & Katzmarzyk, P. T. (2012). Effect of physical inactivity on major non-communicable diseases worldwide: An analysis of burden of disease and life expectancy. *The Lancet*, 380(9838), 219–229. [https://doi.org/10.1016/S0140-6736\(12\)61031-9](https://doi.org/10.1016/S0140-6736(12)61031-9)
- Luthar, S. S., Cicchetti, D., & Becker, B. (2000). The construct of resilience: A critical evaluation and guidelines for future work. *Child Development*, 71(3), 543–562.
- McKee, G., Mooney, M., O'Donnell, S., O'Brien, F., Biddle, M. J., & Moser, D. K. (2019). A cohort study examining the factors influencing changes in physical activity levels following an acute coronary syndrome event. *European Journal of Cardiovascular Nursing*, 18(1), 57–66. <https://doi.org/10.1177/1474515118786203>
- Namazi, H. (2021). Complexity and information-based analysis of the heart rate variability (HRV) while sitting, hand biking, walking, and running. *Fractals*, 29, Article 2150201. <https://doi.org/10.1142/S0218348X21502017>, 05.
- Obón-Santacana, M., Vilardell, M., Carreras, A., Duran, X., Velasco, J., Galván-Femenía, I., ... Cid, R. de. (2018). GCAT|Genomes for life: A prospective cohort study of the genomes of Catalonia. *BMJ Open*, 8(3), Article e018324. <https://doi.org/10.1136/bmjopen-2017-018324>
- Olthof, M., Hasselman, F., Strunk, G., van Rooij, M., Aas, B., Helmich, M. A., Schiepek, G., & Lichtwarck-Aschoff, A. (2020). Critical fluctuations as an early-warning signal for sudden gains and losses in patients receiving psychotherapy for mood disorders. *Clinical Psychological Science*, 8(1), 25–35. <https://doi.org/10.1177/2167702619865969>
- Oud, J. H. L., & Voelkle, M. C. (2014). Do missing values exist? Incomplete data handling in cross-national longitudinal studies by means of continuous time modeling. *Quality and Quantity*, 48(6), 3271–3288. <https://doi.org/10.1007/s11135-013-9955-9>
- Pruessner, J. C., Kirschbaum, C., Meinlschmid, G., & Hellhammer, D. H. (2003). Two formulas for computation of the area under the curve represent measures of total hormone concentration versus time-dependent change. *Psychoneuroendocrinology*, 28(7), 916–931. [https://doi.org/10.1016/S0306-4530\(02\)00108-7](https://doi.org/10.1016/S0306-4530(02)00108-7)
- R Core Team. (2021). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing. <https://www.R-project.org/>.
- Richardson, G. E. (2002). The metatheory of resilience and resiliency. *Journal of Clinical Psychology*, 58(3), 307–321. <https://doi.org/10.1002/jclp.10020>
- Scheffer, M., Bolhuis, J. E., Borsboom, D., Buchman, T. G., Gijzel, S. M. W., Goulson, D., Kammenga, J. E., Kemp, B., van de Leemput, I. A., Levin, S., Martin, C. M., Melis, R. J. F., van Nes, E. H., Romero, L. M., & Olde Rikkert, M. G. M. (2018). Quantifying resilience of humans and other animals. *Proceedings of the National Academy of Sciences*, 115(47), 11883–11890. <https://doi.org/10.1073/pnas.1810630115>
- Smith, B. W., Dalen, J., Wiggins, K., Tooley, E., Christopher, P., & Bernard, J. (2008). The brief resilience scale: Assessing the ability to bounce back. *International Journal of Behavioral Medicine*, 15(3), 194–200. <https://doi.org/10.1080/1070550080222972>
- Stadnitski, T., & Wild, B. (2019). How to deal with temporal relationships between biopsychosocial variables: A practical guide to time series analysis. *Psychosomatic Medicine*, 81(3), 289–304. <https://doi.org/10.1097/PSY.0000000000000680>
- Wagner, A. L., Keusch, F., Yan, T., & Clarke, P. J. (2019). The impact of weather on summer and winter exercise behaviors. *Journal of Sport and Health Science*, 8(1), 39–45. <https://doi.org/10.1016/j.jshs.2016.07.007>
- Wickham, H., Averick, M., Bryan, J., Chang, W., McGowan, L. D., François, R., Grolemund, G., Hayes, A., Henry, L., Hester, J., Kuhn, M., Pedersen, T. L., Miller, E., Bache, S. M., Müller, K., Ooms, J., Robinson, D., Seidel, D. P., Spinu, V., ... Yutani, H. (2019). Welcome to the tidyverse. *Journal of Open Source Software*, 4(43), 1686. <https://doi.org/10.21105/joss.01686>
- Windle, G. (2011). What is resilience? A review and concept analysis. *Reviews in Clinical Gerontology*, 21, 152–169. <https://doi.org/10.1017/S0959259810000420>
- Winter, B., & Wieling, M. (2016). How to analyze linguistic change using mixed models, growth curve analysis and generalized additive modeling. *Journal of Language Evolution*, 1(1), 7–18. <https://doi.org/10.1093/jole/lzv003>
- Wood, S. N. (2011). Fast stable restricted maximum likelihood and marginal likelihood estimation of semiparametric generalized linear models. *Journal of the Royal Statistical Society: Series B*, 73(1), 3–36. <https://doi.org/10.1111/j.1467-9868.2010.00749.x>
- Wood, S. N. (2017). *Generalized additive models: An introduction with R* (2nd ed.). Chapman and Hall/CRC. <https://doi.org/10.1201/9781315370279>