OPEN ACCESS

PUCRS ESCOLA DE MEDICINA

SCIENTIA MEDICA

Scientia Medica Porto Alegre, v. 32, p. 1-8, jan.-dez. 2022
e-ISSN: 1980-6108 | ISSN-L: 1806-5562

http://dx.doi.org/10.15448/1980-6108.2022.1.43237

SEÇÃO: EDUCATION IN HEALTH SCIENCES

# Pain and physical activity for one individual: a comparison of models

*Dor e atividade física para um indivíduo: uma comparação de modelos*

**Jimmie Leppink**[1]
orcid.org/0000-0002-8713-1374
j.leppink@gmail.com

**Received on:** May. 10th, 2022
**Approved on:** Jun, 17th, 2022
**Published on:** Dec, 5th, 2022.

## Abstract

**Aims:** there is increasing awareness that for effective patient care we need more than only randomized controlled trials with groups of participants and that carefully collected single case ($N = 1$) data have several important advantages over traditional group-level studies. With the advance of technology, collecting relevant data from a single case is becoming easier by the day, and this offers tremendous opportunities for understanding how behaviors displayed by an individual can be influenced by one or several key variables. For example, how pain experienced influences the amount of time spent on physical exercise.

**Method:** using publicly available observational single case data, five models are compared: a classical ordinary least squares (OLS) linear regression model; a dynamic regression model (DRM); a two-level random-intercepts model (2LRI); a continuous covariate first-order autoregressive correlation model (CAR1); and an ordinary least squares model with time trend (OLST). These models are compared in terms of overall model fit statistics, estimates of the relation between physical activity (response variable of interest) and pain (covariate of interest), and residual statistics.

**Results:** 2LRI outperforms all other models on both overall model fit and residual statistics, and provides covariate estimates that are in between the relative extremes provided by other models. CAR1 and OLST demonstrate an almost identical performance and one that is substantially better than OLS – which performs worst – and DRM.

**Conclusion:** for observational single case data, DRM, CAR1, OLST, and 2LRI account for the serial correlation that is typically present in single case data in somewhat different ways under somewhat different assumptions, and all perform better than OLS. Implications of these findings for observational, quasi-experimental, and experimental single case studies are discussed.

**Keywords:** autoregressive correlation models, dynamic regression modeling, multilevel modeling, observational research, single case data.

## Resumo

**Objetivos:** há uma crescente conscientização de que, para um atendimento eficaz ao paciente, precisamos de mais do que apenas ensaios clínicos randomizados com grupos de participantes e que os dados de caso único cuidadosamente coletados (N = 1) têm várias vantagens importantes sobre os estudos tradicionais em nível de grupo. Com o avanço da tecnologia, coletar dados relevantes de um único caso está se tornando mais fácil a cada dia, e isso oferece enormes oportunidades para entender como os comportamentos exibidos por um indivíduo podem ser influenciados por uma ou várias variáveis-chave. Por exemplo, como a dor experimentada influencia a quantidade de tempo gasto no exercício físico.

**Método:** usando dados de caso único observacionais disponíveis publicamente, cinco modelos são comparados: um modelo clássico de regressão linear de mínimos quadrados ordinários (OLS); um modelo de regressão dinâmica (DRM); um modelo de interceptações aleatórias de dois níveis (2LRI); um modelo de correlação autorregressiva de primeira ordem covariável contínua (CAR1); e um



[1] Hospital virtual Valdecilla (HvV), Santander, Cantabria, Spain.

modelo ordinário de mínimos quadrados com tendência temporal (OLST). Esses modelos são comparados em termos de estatísticas gerais de ajuste do modelo, estimativas da relação entre atividade física (variável de resposta de interesse) e dor (covariável de interesse) e estatísticas residuais.

**Resultados:** o 2LRI supera todos os outros modelos tanto no ajuste geral do modelo quanto nas estatísticas residuais e fornece estimativas de covariáveis que estão entre os extremos relativos fornecidos por outros modelos. CAR1 e OLST demonstram um desempenho quase idêntico e substancialmente melhor que o OLS, que apresenta o pior desempenho, e o DRM.

**Conclusão:** para dados observacionais de caso único, DRM, CAR1, OLST e 2LRI são responsáveis pela correlação seriada que normalmente está presente em dados de caso único de maneira um pouco diferentes sob suposições um pouco diversas, e todos têm um desempenho melhor que o OLS. Implicações dessas descobertas para estudos de caso único observacionais, quase-experimentais e experimentais são discutidas.

**Palavras-chave:** modelos de correlação autorregressiva, modelagem de regressão dinâmica, modelagem multinível, pesquisa observacional, dados de caso único.

## Introduction

If we take a random sample of *N* = 100 individuals from different families (i.e., no genetic relations such as twins or siblings) who do not usually interact with each other and ask them how many hours they slept last night, we can normally consider these 100 responses as statistically independent, that is: there is no reason to assume that we can predict the response coming from person A by the response provided by person B. However, if instead we ask *one* individual (*N* = 1) to respond to this question 100 consecutive days, that individual's response most probably depends to some extent on responses provided one or more days before. This dependence is also referred to as *autocorrelation* or *serial correlation* and must be accounted for in order to avoid inadequate model estimates and/or standard errors (1, 2). As McDonald and colleagues (1) eloquently presented, the traditional *ordinary least squares* (OLS) linear regression approach that is often valid in studies involving groups but no repeated measurements (e.g., the example of *N* = 100 mentioned previously) is generally not useful for single case data exactly because it incorrectly assumes no serial correlation. In a 10-step tutorial for beginners, McDonald and colleagues demonstrate a *dynamic regression model* (DRM) (5) and provide a publicly available copy of the single case data used. Both the article and the data sharing are examples of excellent scientific practice, because it allows researchers and practitioners to understand the data, the model presented by the authors, and to run their own models. Although single case data are easy to collect nowadays, the serial correlation and other data features can be quite complex and there may be several models that each perform well but shed light on the same data, with the same research question, under different assumptions. With the latter aim in mind, this article compares five models: OLS, DRM, a two-level random-intercepts model (2LRI), a continuous covariate first-order autoregressive correlation model (CAR1), and an ordinary least squares model with time trend. Each of these models is explained in more detail in the Methods section. Although these five models have their own assumptions, pros and cons, the research question is the same as was used by McDonald and colleagues (1), namely whether pain measured today influences physical activity levels in the next 24 hours.

## Method

In the dataset provided by McDonald et al. (1), the continuous outcome variable of interest was the number of minutes spent on *physical activity* in a 24-hour time window, and there was a covariate *pain* measured on a scale from 0 (no pain at all) to 10 (extreme pain). The participant in this study was a 39-year-old man who had chronic and unexplained muscle and joint pain, and provided data for this study for 87 consecutive days. Since these and other details of the study are described in the Open Access available article by McDonald and colleagues, the remainder of this section focusses on the models compared. All models compared in this article treat physical activity as outcome variable and pain as a linear covariate but differ in the way serial correlation is dealt with.

In the OLS model serial correlation is ignored,

while in DRM (a reproduction of McDonald et al. (1)) serial correlation is accounted for by using physical activity reported the day before (lag 1) and two days before (lag 2) as linear covariates (along with pain), and in the OLST model a period-dependent time trend is used to account for serial correlation as indicated in **Figure 1**. As indicated in figure 1, OLST includes in its regression model (along with pain) the period-specific (block-specific) time trend.

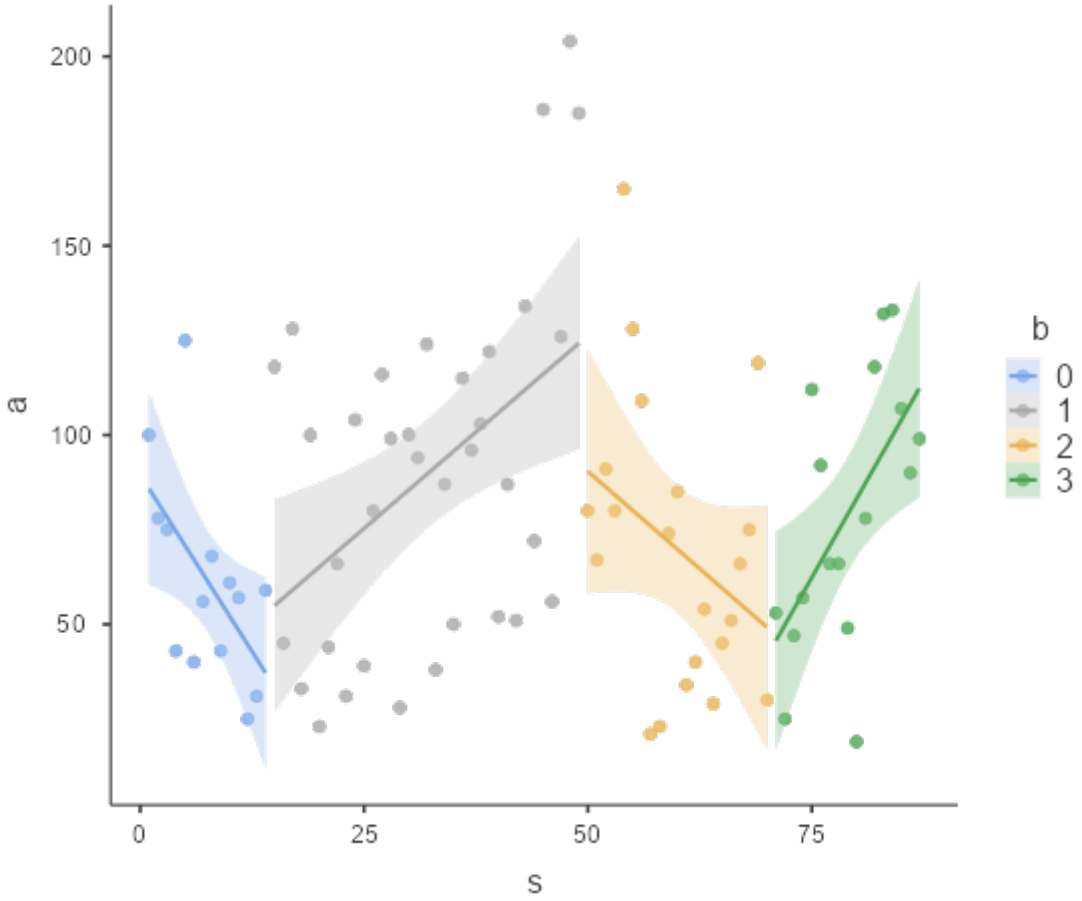


**Figure 1.** Physical activity (a) and its trend across study days (s): block (b) 0 being days 1-14 (weeks 1-2), block 1 being days 15-49 (weeks 3-7), block 2 being days 50-70 (weeks 8-10), and block 3 being days 71-87 (the last ca. 2.5 weeks of study).

In 2LRI, serial correlation is accounted for by means of a random time trend, through the *week*-level random intercept as a random effect; this model assumes that the relation between physical activity and pain is comparable across weeks, but that there is a random process contributing to changes in physical activity over time that results in differences in intercept for the relation between physical activity and pain across weeks.

The fourth model, CAR1, is effectively an extension of AR1 (2) but dealing with a continuous covariate (6), that is: if the covariate(s) of interest were categorical – for example before vs. after an intervention – AR1 could be sufficient (2, 7), but since pain can be considered a continuous covariate CAR1 can be considered more appropriate. The time trend is the same as for OLST.

All statistical analyses were carried out in the *Rj* editor version 1.1.0 in *jamovi* version 2.3 (8) – a module that enables users who have both *R* (9) and *jamovi* installed to run *R* from within *jamovi* – using the *nlme* package version 3.1-157 (7) for

CAR1 and using the *GAMLj* package version 2.6.4 (10) for the other models.

**Table 1** presents the outcomes of the five models compared.

## Results

**TABLE 1 –** Five models compared on the McDonald et al. [1] data in terms of overall model fit statistics, covariate estimates, and residual (DW = Durbin-Watson) and/or random-effect statistics.

| | model | | | | |
|---|---|---|---|---|---|
| **criterion** | **OLS** | **DRM** | **2LRI** | **CAR1** | **OLST** |
| overall | | | | | |
| $R^2$ | 0.049 | 0.162 | 0.396 | 0.346 | 0.346 |
| AIC | 890.835 | - | 865.384 | - | 872.234 |
| BIC | 898.232 | - | 877.597 | - | 896.893 |
| covariate | | | | | |
| *B* | -53.050 | -59.856 | -59.055 | -68.889 | -69.502 |
| *SE* | 25.455 | 24.784 | 23.047 | 23.855 | 23.676 |
| *p*-value | 0.040 | 0.018 | 0.012 | 0.005 | 0.004 |
| residuals | | | | | |
| *M* | 0.000 | 0.000 | 0.000 | < 0.001 | 0.000 |
| *SD* | 39.334 | 37.287 | 31.948 | 32.615 | 32.614 |
| DW $r_A$ | 0.252 | 0.045 | -0.091 | -0.053 | -0.054 |
| DW statistic | 1.489 | 1.907 | 2.177 | 2.102 | 2.104 |
| DW *p*-value | 0.014 | 0.606 | 0.456 | 0.652 | 0.784 |
| random terms | | | | | |
| *ICC* | - | - | 0.263 | - | - |
| *ICC p*-value | - | - | < 0.001 | - | - |
| *CAR1* statistic | - | - | - | 0.043 | - |
| *CAR1* 95% LB | - | - | - | < 0.001 | - |
| *CAR1* 95% UB | - | - | - | 0.928 | - |

*2LRI, two-level random-intercepts model; CAR1, continuous first-order autoregressive correlation model; DRM, dynamic regression model; DW, Durbin-Watson; ICC, intraclass correlation coefficient*; *OLS, ordinary least squares model; OLST, ordinary least squares model with time trend*

Table 1 clearly indicates that OLS performs worst and 2LRI performs best. A comparison of all five models in terms of Akaike's (11) and Schwarz Bayesian (12) information criteria (AIC, BIC) would be possible if all five models used the same type of model estimator and exactly the same data (13, 14) but in the current study that is only the case for OLS, 2LRI, and OLST. A

complication with DRM is that, using lag 1 data results in a missing value in the lag 1 covariate on the first observation, and using lag 2 data creates missing values in the lag 2 covariate on the first two observations, hence in this case losing the first two observations. One could argue that for this reason also a comparison in terms of $R^2$ can be somewhat tricky. Next, in the case of CAR1, restricted maximum likelihood (REML) is used as an estimator and that makes any kind of comparison in terms of AIC or BIC tricky (13). However, in terms of both $R^2$ and residual statistics, CAR1 and OLST perform almost identically, and their predictions are almost the same ($r > 0.999$, with near-0 absolute differences). In terms of both $R^2$ and, to the extent that comparison allows, AIC and BIC, the best performing model is 2LRI, and **Figure 2** therefore presents the observed and the 2LRI-predicted relation between physical activity and study day using.

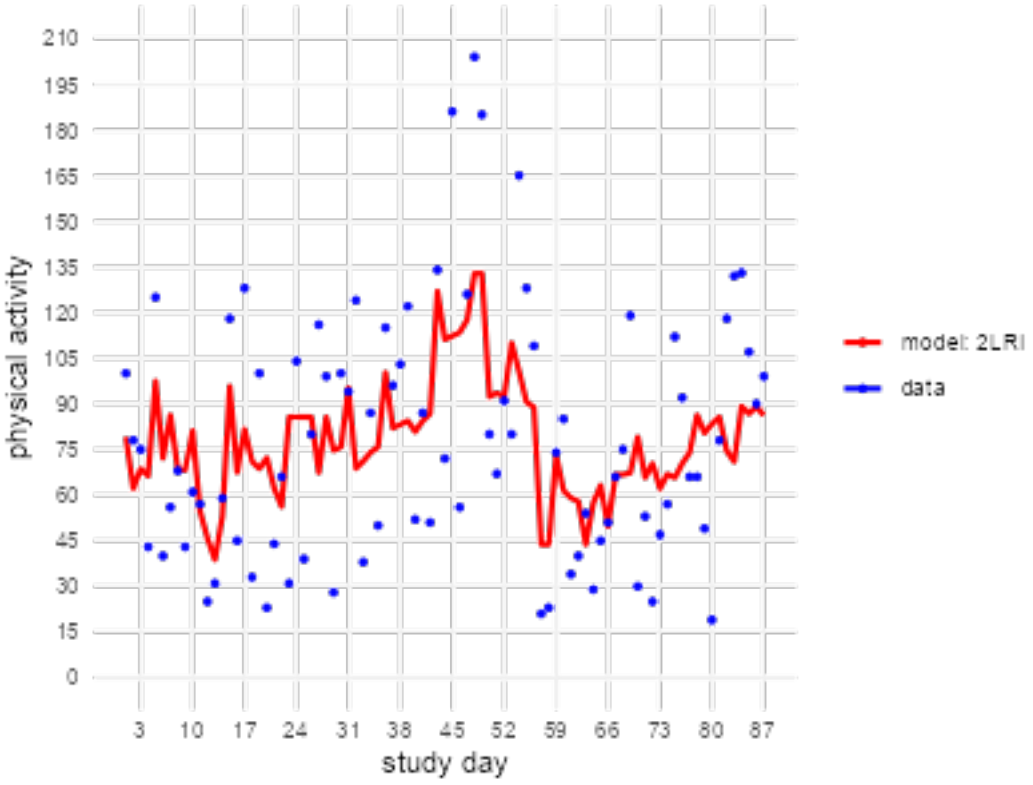


**Figure 2.** Physical activity and its trend across study days: observed (data, blue) and predicted (two--level random-intercepts model, 2LRI, red).

The only model with a statistically significant Durbin-Watson statistic (15) is OLS, which is the only model that completely ignores the serial correlation. The other four models each appear to account appropriately for serial correlation, albeit it each in a somewhat different way. For the data at hand, CAR1 and OLST yield about the same outcomes, which indicates that the additional account for serial correlation through AR1 for a continuous covariate (which now has a point estimate of 0.043 and a very wide 95% confidence interval) – the only difference between these two models – is not needed.

2LRI results in an intra-class coefficient (ICC) of 0.263 ($p < 0.001$), which estimates the strength of the random effect, here week-level random intercept. Its predicted values explain nearly 40% of the variance in physical activity ($R^2$ = 0.396, higher is better), it has the lowest AIC and BIC (lower is better), it results in the lowest residual standard deviation, and it provides estimates for the pain covariate that are in between the relative

extremes of OLS (point estimate of -53.050) and CAR1/OLST (point estimates around -69) and very similar to DRM. As an extra check on the residuals, **Figure 3** presents the autocorrelation function of the residuals resulting from 2LRI.

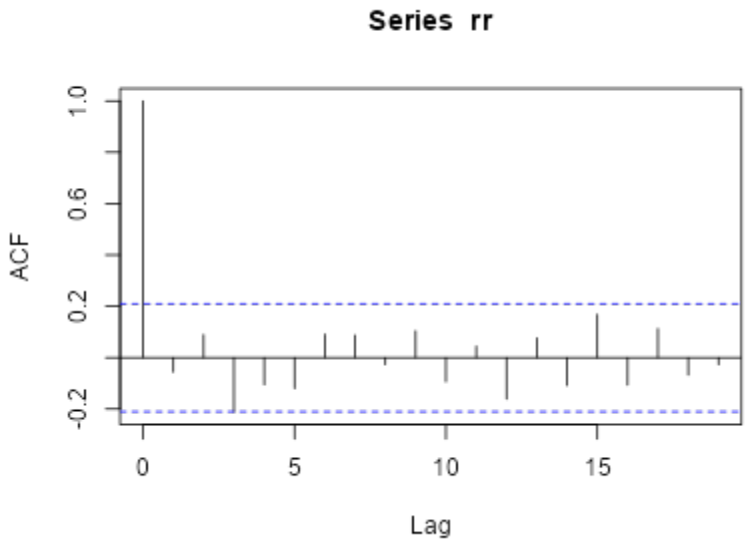


**Figure 3.** Autocorrelation function of the residuals resulting from the two-level random-intercepts model (2LRI).

Figure 3 indicates no substantial autocorrelation to be accounted for in addition to what has been accounted for with 2LRI.

## Discussion

Although with the current data, shared by McDonald and colleagues (1), 2LRI outperforms the other models, it is very well possible that with another dataset the order of models in terms of performance is different, with for example DRM outperforming other models. In the end, all five models presented in this article provide the same answer to the research question: *yes*, pain measured today appears to influence physical activity levels in the next 24 hours. The goal of this article is not to demonstrate or conclude that 2LRI is a better model than DRM that was presented by McDonald et al. (1) but to provide an example of a range of models that may shed some light on the same research question under somewhat different assumptions. In the remainder of this article, pros and cons of each of the five models compared are discussed.

### *OLS: an easy to use model for control comparisons in observational single case studies*

As explained in the literature (e.g., (1-7, 13, 14)) and as demonstrated in this article, OLS is unlikely to account for serial correlation in an appropriate manner, because it assumes no serial correlation while in practice serial correlation is a natural phenomenon in single case data. However, it can serve as a control comparison in observational studies like the one introduced by McDonald et al. (1) and reanalyzed with a range of models in this article, in the sense that it can help to provide evidence that a more complex model is needed to account for serial correlation. For example, in this article, OLS underperforms relative to all four alternatives.

### *DRM: likely a reasonable model for observational single case data*

As already explained by McDonald et al. (1), DRM can be considered a better alternative to OLS when dealing with observational single case data. It is effectively just an OLS model with at least one lagged covariate and is therefore easy to use and interpret like other OLS models. A main limitation of DRM relative to the other models discussed in this article is the missing data in the first observation(s) due to missingness in the lagged covariates. Although this data loss may not be much of an issue in series of the size in the example discussed (87 complete observations being reduced to 85), it may cause difficulties when smaller series ($N < 50$) are to be analyzed.

### *2LRI: another possibly reasonable model for observational single case data*

As indicated in this article, 2LRI can provide a better alternative to OLS when dealing with observational single case data. Using a 'seasonal' factor – in this example 'week' but in other examples it might well be 'month', 'quarter' or 'year') – as random effect, it allows the relation between outcome variable (here: physical activity) and time (here: study day) to change in a non-linear and random fashion, without having to identify periods of time (blocks) as in CAR1 or OLST. A limitation that 2LRI and DRM have in common that they are likely difficult to use in substantially smaller series, albeit for different reasons. In the case of 2LRI, the random intercepts are assumed to be distributed (approximately) normally; for the data at hand (87 observations) that assumption can be checked and appears realistic, yet if we were to deal with a series of only 7 weeks of daily data we would have only 7 random intercepts and it would be difficult to meaningfully check the assumption.

### *CAR1 and OLST: perhaps more useful for (quasi-)experimental single case data*

In cases such as in the example discussed in this article, where a scatterplot can relatively easily indicate time periods (blocks), CAR1 and OLST may provide good models for observational data. However, in many cases, defining such periods may be difficult and somewhat arbitrary unless specific events occur and/or solid theory is available. For example, if in a series of 50 observations there is an intervention after 25 observations to which the outcome variable of interest may well respond with a change in trajectory, we are dealing with a quasi-experimental study in which observations 1-25 and observations 26-50 can be defined as two blocks in a nonarbitrary manner. Likewise, if we have 10 participants who each have 50 observations but receive that intervention at a different point in time determined in a random manner, we deal with single case experimental data, and for each participant the series before and after the intervention can be defined as two different blocks. If no covariate other than time is available, not CAR1 but AR1 can be considered and that will likely be a better candidate than OLST because it can account for both serial correlation and unequal variance (2, 6, 7).

## Notes

The author wishes to thank Dr Suzanne McDonald, Dr Rute Vieira, and Dr Derek W. Johnston for publicly sharing their data along with their article in Health Psychology and Behavioral Medicine in 2020 and for documenting their model and all the steps taken in such detail. In the end, all models we use are mere simplifications of phenomena in the complex and dynamic world around us, but data sharing can greatly help researchers and practitioners to study the same data from different perspectives and assumptions and as such gain a little bit more understanding of the phenomena we are interested in.

## Funding

This study did not receive financial support from external sources

## Conflicts of interest disclosure

The authors declare no competing interests relevant to the content of this study.

## Author contribution

The author declares to have made substantial contributions to the conception, or design, or acquisition, or analysis, or interpretation of data; and drafting the work or revising it critically for important intellectual content; and to approve the version to be published.

## Availability of data and responsibility for the results

All the authors declare to have had full access to the available data and they assume full responsibility for the integrity of these results.

## References

1. McDonald S, Vieira R, Johnston DW. Analysing N-of-1 observational data in health psychology and behavioural medicine: a 10-step SPSS tutorial for beginners. Health Psych Behav Med. 2020;8(1):32-54. https://doi.org/10.1080/21642850.2019.1711096

2. Van de Schoot R, Miocevic M. Small sample size solutions: a guide for applied researchers and practitioners. New York: Routledge; 2020. https://library.oapen.org/handle/20.500.12657/22385

3. Leppink J. Bridging research and practice in health professions education: single case designs. As Pac Sch. 2022;7(1):109-11. https://doi.org/10.29060/TAPS.2022-7-1/PV2558

4. Samsung. Enhance your life with Samsung Health. [Internet]. [place unknown]: Samsung; [cited 2022 May 10]. Available from: https://www.samsung.com/global/galaxy/apps/samsung-health

5. Vieira R, McDonald S, Araujo-Soares V, Sniehotta FF, Henderson R. Dynamic modelling of n-of-1 data: powerful and flexible data analytics applied to individualised studies. Health Psych Rev. 2017;11(3):222-34. https://doi.org/10.1080/17437199.2017.1343680

6. Pinheiro J, Bates D, DebRoy S, Sarkar D, Team RC. nlme: linear and nonlinear mixed effects models, R Project: 2021 (version 3.1-157) [Internet]. [place unknown]; [cited 2022 May 10]. Available from: https://cran.r-project.org/web/packages/nlme/nlme.pdf

7. Leppink J. Small numbers are an opportunity, not a problem. Sci Med. 2021;31(1): e40128. https://doi.org/10.15448/1980-6108.2021.1.40128

8. The jamovi project. jamovi (version 2.3) [Computer Software] [Internet]. [place unknown]; [cited 2022 May 10]. Available from: https://doi.org/jamovi.org

9. R Core Team. R: a language and environment for statistical computing (version 4.1) [Computer Software] [Internet]. [place unknown]; [ cited 2022 May 10]. Available from: https://cran.r-project.org

10. Gallucci M. *GAMLj: general analyses for linear models* (version 2.6.4) [Internet]. [place unknown]; [ cited 2022 May 10]. Available from: https://gamlj.github.io/

11. Akaike H. Information theory and an extension of the maximum likelihood principle. In: Petrov BN, Csaki F, editors. Proceedings of the Second International Symposium on Information Theory; Budapest: Academiai Kiado; 1973. p. 267-81.

12. Schwarz G. Estimating the dimensions of a model. Ann Stat. 1978;6:461-4. https://www.jstor.org/stable/2958889

13. Leppink J. Statistical methods for experimental research in education and psychology. Cham: Springer; 2019. https://doi.org/10.1007/978-3-030-21241-4

14. Leppink J. The art of modelling the learning process: uniting educational research and practice. Cham: Springer; 2020. https://doi.org/10.1007/978-3-030-43082-5

15. Durbin J, Watson GS. Testing for serial correlation in least squares regression. Biomet. 1950;37(3-4):409-28. https://doi.org/10.1093/biomet/37.3-4.409

## Jimmie Leppink

PhD in Statistics Education, LLM in Forensics, Criminology and Law; MSc in Psychology and Law from Maastricht University, the Netherlands; MSc in Statistics from Catholic University of Leuven, Belgium. Currently Research Director at Hospital virtual Valdecilla (HvV), in Santander, Spain.

## Mailing address

Jimmie Leppink

Hospital virtual Valdecilla

Avenida de Valdecilla, s/n

Santander, 39008

Spain

*Os textos deste artigo foram revisados pela Poá Comunicação e submetidos para validação do autor antes da publicação.*