

## 4 Conclusion

Generalized additive models provide an intuitive and flexible approach to modelling the repeating signals common to medical monitoring data. We hope researchers will use this introduction as a starting point for including GAMs in their data analyses. Both to answer specific research questions, and as a tool to explore and visualise the cardiac effects and respiratory effects on hemodynamic measurements and the effect of heart–lung interactions.

## 5 Recommended reading

*Generalized Additive Models, An Introduction with R* by Simon Wood [29].

GAMs in R by Noam Ross, A Free, Interactive Course using mgcv (<https://noamross.github.io/gams-in-r-course/>).

*Modelling Palaeoecological Time Series Using Generalised Additive Models* [20]. An introduction to GAMs with a more detailed description of the statistical considerations related to modelling time series and the inferences that can be drawn from the models.

*Hierarchical generalized additive models in ecology: an introduction with mgcv* [30]. The present paper only describes models fitted to data from one individual. A relevant next step is to fit one model across multiple individuals.

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## Declarations

**Conflict of interest** STV is associate editor of Journal of Clinical Monitoring and Computing. JE and GLS report no competing interests.

**Ethical approval** Data was recorded as part of a project registered on ClinicalTrials.gov, NCT04298931 with regional ethical committee approval, case: 1-10-72-245-19.

**Informed consent** All participants provided written informed consent.

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