

## *Syllabus*

# Improving the credibility of future research II: Improving your statistical inferences through simulation studies in R

Simulation studies help demystify the 'whys' and 'hows' behind statistical rules, make sense of  $p$ -values, and allow you to make robust, informed decisions in your research. Many of our statistical practices are based on useful rules: We use a cut-off of  $p$  smaller than 0.05 for determining whether results are statistically significant; we know that larger sample sizes are better; we know that our statistical tests have assumptions that that it is important not to violate them. But why? What even is a  $p$ -value? How are they distributed? If I do violate an assumption, what exactly happens?

Monte Carlo simulation studies involve generating data that mirrors real-world scenarios and then running our statistical tests on this simulated data repeatedly, thereby allowing us to see how the outcomes across various conditions. By simulating many different scenarios, each a large number of times, simulation studies can give us a comprehensive understanding of how our statistical tools behave, what results are possible or likely to observe, and why certain practices are recommended or not.

This course is taught in English and assumes some familiarity with data wrangling in R, such as that covered in my other course taught in the Autumn semester: "Improving the credibility of future research I: Digital project management, data wrangling and visualization". This course does not require that you already feel expert in R, but it does require that you *want to become expert* in R. If you have not taken the required previous course on data wrangling but feel that you have the necessary skills, please contact me for an exception.

## BASIC INFORMATION

### Type

Seminar

### Level

Master

### ECTS

5

### Mode

Weekly meetings with take home preparatory and practice exercises.

### Learning Goals

By the end of the course, students will be able to:

- Understand the fundamental principles and concepts of Monte Carlo simulation studies.
- Design, implement, and interpret Monte Carlo simulations using R and tidyverse packages (dplyr, tidyr, purrr) for various statistical scenarios encountered in psychological research.
- Evaluate the performance of statistical tests under different conditions such as varying sample sizes, effect sizes, and distributional assumptions.
- Apply Monte Carlo simulation study methods to enhance power analysis, model evaluation, and parameter estimation.
- Critically appraise published psychological research that employs Monte Carlo simulations.

### Assessment

- 3 at-home assignments during the teaching term. Your best two grades from these assignments go towards your grade. These two assignments count for 20% of your final grade each (40% total).
- 1 end-of-class assignment to be completed by <<date to be mutually agreed with students>>. This assignment counts for 60% of your final grade.
- You must attend or have excused absences for at least 80% of the lessons (i.e., no more than two unexcused absences) to be able to pass the course.
- All code assessments must include a heading noting that they are under a CC-BY 4.0 license. The reason for this is that a) the materials issued to you as part of the course are also CC BY 4.0 licensed and freely available for others to use or modify with attribution, and b) I want to allow for the possibility that the simulations you write as part of the course could further contribute to this open source resource for others to benefit from in future. For example, I suggest that you include the following heading and URL:

```
# License
```

```
[CC BY 4.0](https://creativecommons.org/licenses/by/4.0/deed.en)
```

### Communication

I will distribute materials and communicate predominantly via Slack. You will receive an invitation to the course's Slack channel via your UniBe email account. Please contact me via slack rather than email where possible, except for excused absences from class which should be via email.

### Materials

I will distribute code and slides via Slack each week for the material covered in class, as well as any preparatory or practice exercises or assignments.

WISSEN  
SCHAFFT  
WERT.

You can also find the materials for last year's course on GitHub if you'd like to work ahead into future weeks yourself. Please note the order and content of the weeks is liable to change between years.  
<https://github.com/ianhussey/simulation-course>

## SCHEDULE

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#	Date	Topic
1	19.02.2025	Introduction + foundational concepts
2	26.02.2025	Writing functions
3	05.03.2025	General structure of a simulation
4	12.03.2025	Factorial vs. one-at-a-time simulations
5	19.03.2025	Understanding $p$ -values
6	26.03.2025	Hidden multiplicity in ANOVA
7	02.04.2025	What does it mean to violate assumptions?
8	09.04.2025	<<Probably no class - Ian at a conference. To be confirmed.>> Otherwise: Simulating causal models
9	16.04.2025	The difference between significant and non-significant is not itself significant
	23.04.2025	No class (spring break)
10	30.05.2025	Understanding Confidence Intervals via sequential testing
11	07.05.2025	Should we test our statistical assumptions?
12	14.05.2025	How standardized are 'standardized' effect sizes?
13	21.05.2025	Meta-analysis and bias
14	28.05.2025	The impact of careless responding on correlations

The content and pacing of the course will be adapted, to some degree, to students' needs and wants. There is a selection of other topics that we could cover instead of the listed topics if you prefer, including:

- Simulating individual datasets that meet the specific experimental design of your real-world study to allow you to write your analysis code before the data is collected.
- The impact of different  $p$ -hacking strategies on false positive rates.
- The impact of different data tampering strategies on false positive rates.
- Why most psychology research is statistically unfalsifiable.
- The reliability paradox: why unreliable measures can sometimes produce replicable effects
- How confounding can produce replicable but incorrect conclusions.
- Using simulation studies to understand Bayesian estimation methods and the influence of the choice of prior.
- The impact of confusing SE and SD when extracting effect sizes for meta-analysis
- The efficacy of different methods to correct for bias in meta-analysis