Marburg University

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Simulation studies in psychology: Status quo, problems, and potential solutions

MSMR · August 2026

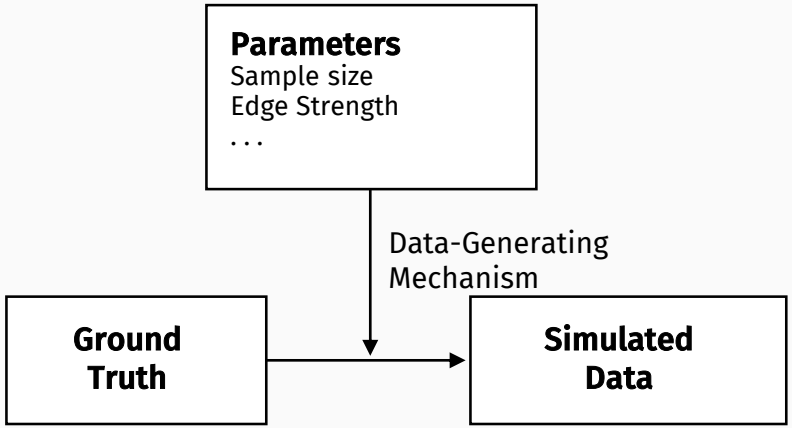
Björn Siepe

Psychological Methods Lab, Department of Psychology, Marburg University

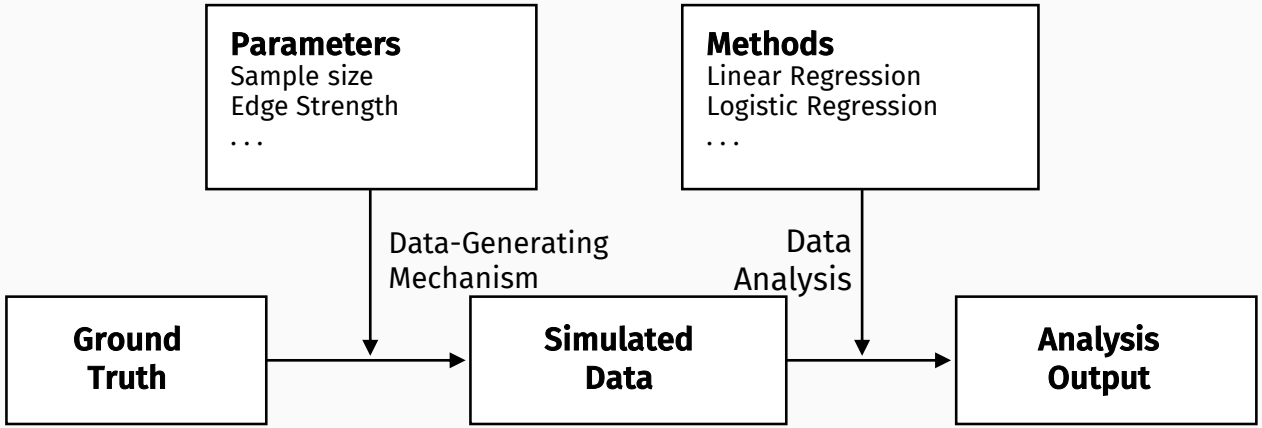
Part I: Background and Issues

Simulation studies

Simulation studies



Simulation studies



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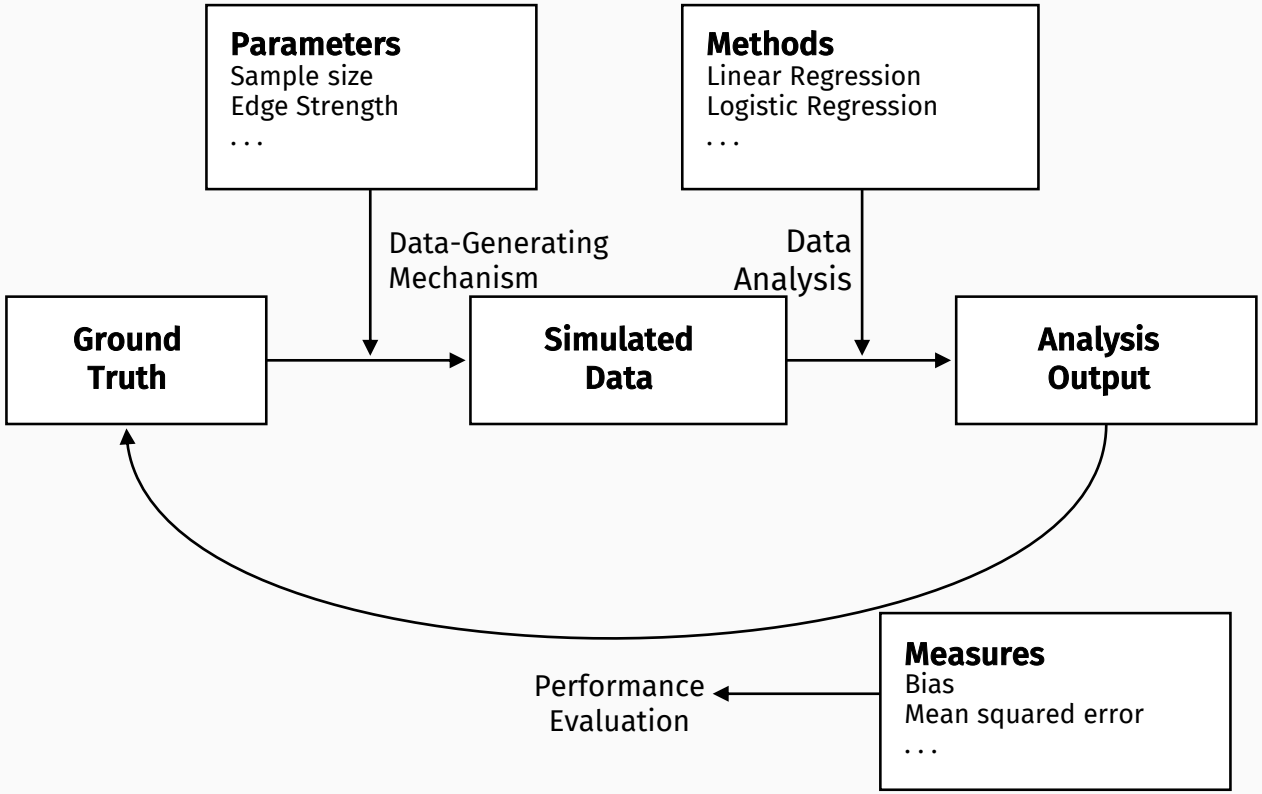

Issues in simulation studies

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Marcin Wichary - Wikimedia

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> **Statisticians ... often pay too little attention to their own principles of design**
>
> Hoaglin & Andrews, 1975

Meta-Science on Simulation Studies

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Studied across **(bio)statistics, ecology, and psychometrics**

e.g., Koehler et al., 2009; Morris et al., 2019; Williams et al., 2024; Feinberg & Rubright, 2016; Bouma et al., 2026

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Many degrees of freedom

Pawel et al., 2024

Over-optimism towards new methods

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Overall: Issues similar to other empirical research

Boulesteix et al., 2020

Simulation studies in psychology

Simulation studies in psychology

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Psychological Methods

ISSN: 1082-989X

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Simulation Studies for Methodological Research in Psychology: A Standardized Template for Planning, Preregistration, and Reporting

Björn S. Siepe[1], František Bartoš[2], Tim P. Morris[3], Anne-Laure Boulesteix[4, 5], Daniel W. Heck[1], and Samuel Pawel[6, 7]

Simulation studies in psychology

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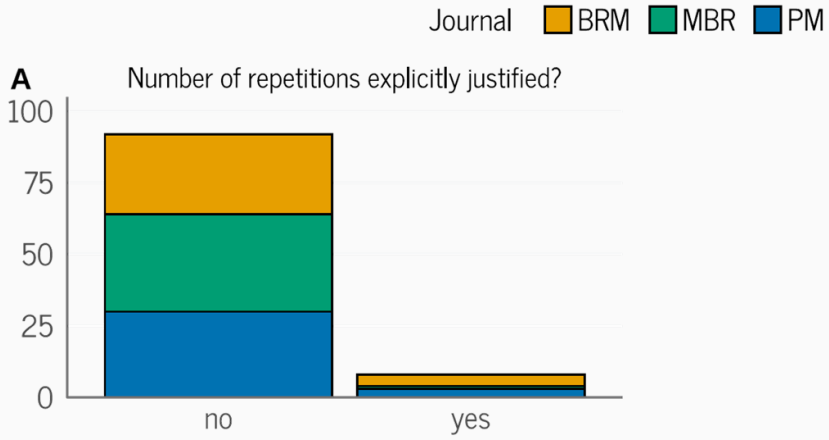

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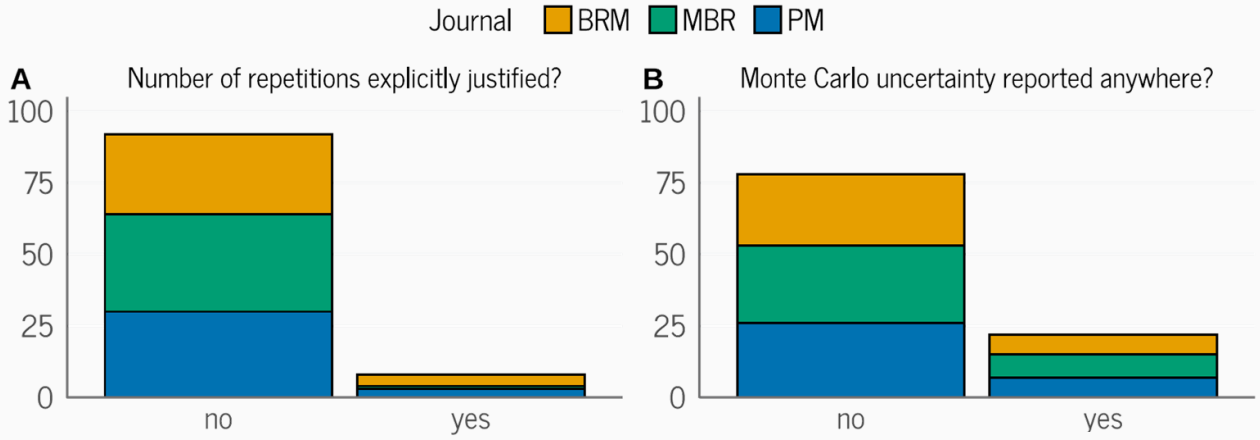

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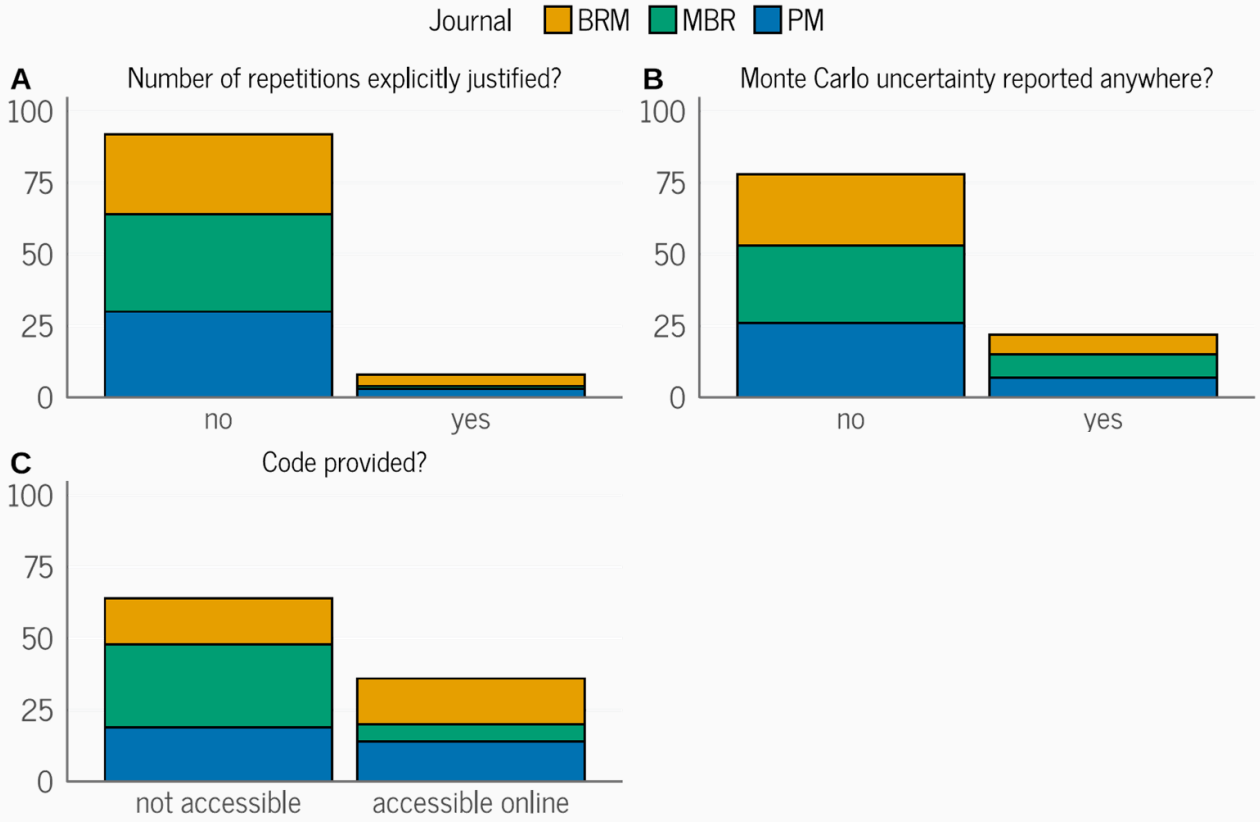

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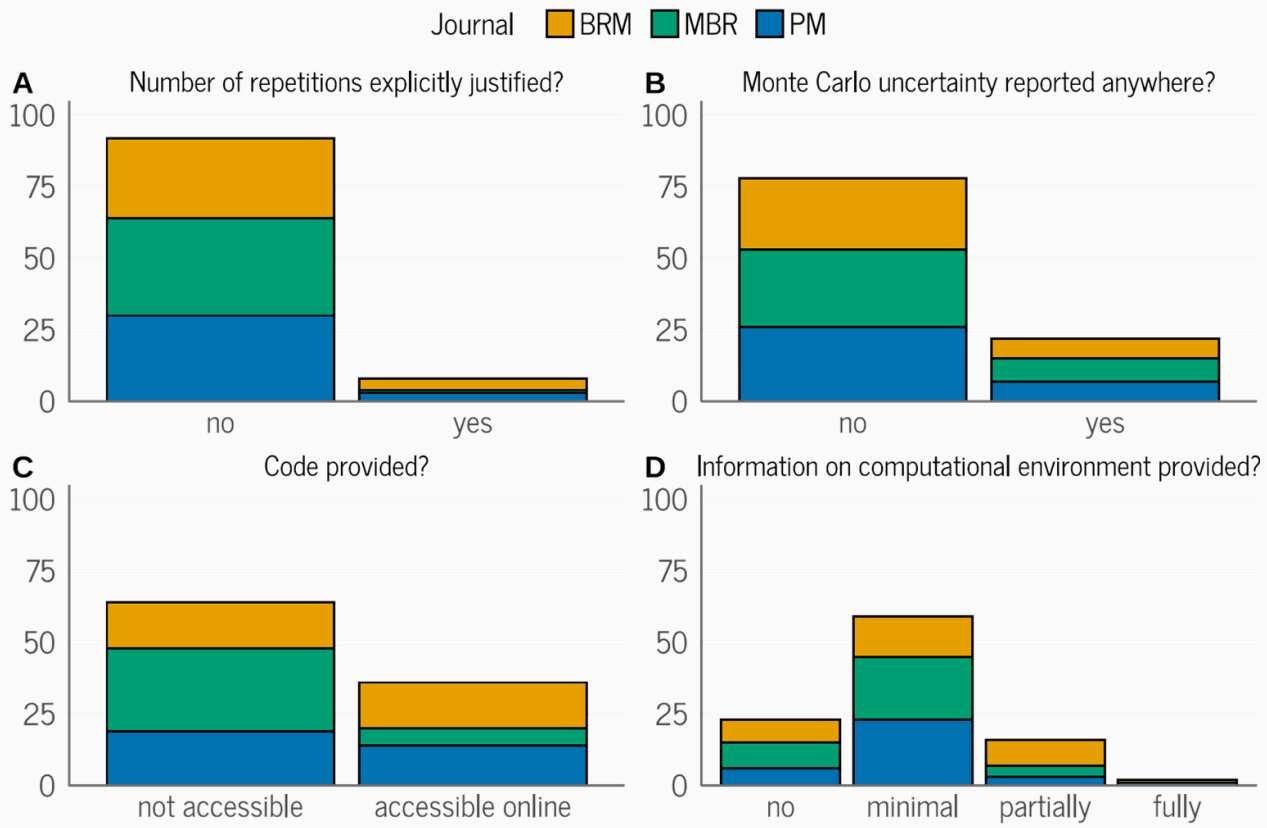

Improving reporting (based on Morris et al., 2019)

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Table 3

Definitions of Common PerformanceMeasures, Their Estimates, MCSEs, and Number of Simulation Repetitions n_{sim} to Achieve a Desired MCSE$_*$ (Morris et al., 2019, Table A1)

Performance measure	Definition	Estimate	MCSE	n_{sim}
Bias	$\mathrm{E}(\hat{\theta}) - \theta$	$(\sum_{i=1}^{n_{\text{sim}}} \hat{\theta}_i / n_{\text{sim}}) - \theta$	$\sqrt{S_{\hat{\theta}}^2 / n_{\text{sim}}}$	$S_{\hat{\theta}}^2 / \text{MCSE}_*^2$
Relative bias	$\{\mathrm{E}(\hat{\theta}) - \theta\}/\theta$	$\{(\sum_{i=1}^{n_{\text{sim}}} \hat{\theta}_i / n_{\text{sim}}) - \theta\}/\theta$	$\sqrt{S_{\hat{\theta}}^2 / (\theta^2 n_{\text{sim}})}$	$S_{\hat{\theta}}^2 / (\text{MCSE}_*^2 \theta^2)$
MSE	$\mathrm{E}\{(\hat{\theta} - \theta)^2\}$	$\sum_{i=1}^{n_{\text{sim}}} (\hat{\theta}_i - \theta)^2 / n_{\text{sim}}$	$\sqrt{S_{(\hat{\theta}-\theta)^2}^2 / n_{\text{sim}}}$	$S_{(\hat{\theta}-\theta)^2}^2 / \text{MCSE}_*^2$
RMSE	$\sqrt{\mathrm{E}\{(\hat{\theta} - \theta)^2\}}$	$\sqrt{\sum_{i=1}^{n_{\text{sim}}} (\hat{\theta}_i - \theta)^2 / n_{\text{sim}}}$	$\sqrt{S_{(\hat{\theta}-\theta)^2}^2 / (4 n_{\text{sim}} \widehat{\text{MSE}})}$	$S_{(\hat{\theta}-\theta)^2}^2 / (4 \widehat{\text{MSE}}\, \text{MCSE}_*^2)$
Empirical variance	$\mathrm{Var}(\hat{\theta})$	$S_{\hat{\theta}}^2$	$S_{\hat{\theta}}^2 \sqrt{2/(n_{\text{sim}} - 1)}$	$1 + 2(S_{\hat{\theta}}^2)^2 / \text{MCSE}_*^2$
Empirical standard error	$\sqrt{\mathrm{Var}(\hat{\theta})}$	$\sqrt{S_{\hat{\theta}}^2}$	$\sqrt{S_{\hat{\theta}}^2 / \{2(n_{\text{sim}} - 1)\}}$	$1 + S_{\hat{\theta}}^2 / (2\text{MCSE}_*^2)$
Coverage	Pr (CI includes θ)	$\sum_{i=1}^{n_{\text{sim}}} \mathbb{1}(\text{CI}_i \text{ includes } \theta)/n_{\text{sim}}$	$\sqrt{\widehat{\text{Cov}}(1 - \widehat{\text{Cov}})/n_{\text{sim}}}$	$\widehat{\text{Cov}}(1 - \widehat{\text{Cov}})/\text{MCSE}_*^2$
Power (or Type I error rate)	Pr (Test rejects H_0)	$\sum_{i=1}^{n_{\text{sim}}} \mathbb{1}(\text{Test}_i \text{ rejects } H_0)/n_{\text{sim}}$	$\sqrt{\widehat{\text{Pow}}(1 - \widehat{\text{Pow}})/n_{\text{sim}}}$	$\widehat{\text{Pow}}(1 - \widehat{\text{Pow}})/\text{MCSE}_*^2$
Mean CI width	$\mathrm{E}(\text{CI}_{\text{upper}} - \text{CI}_{\text{lower}})$	$\sum_{i=1}^{n_{\text{sim}}} (\text{CI}_{i,\text{upper}} - \text{CI}_{i,\text{lower}})/n_{\text{sim}}$	$\sqrt{S_W^2 / n_{\text{sim}}}$	S_W^2 / MCSE_*^2
Mean of generic statistic G	$\mathrm{E}(G)$	$\sum_{i=1}^{n_{\text{sim}}} G_i / n_{\text{sim}}$	$\sqrt{S_G^2 / n_{\text{sim}}}$	S_G^2 / MCSE_*^2

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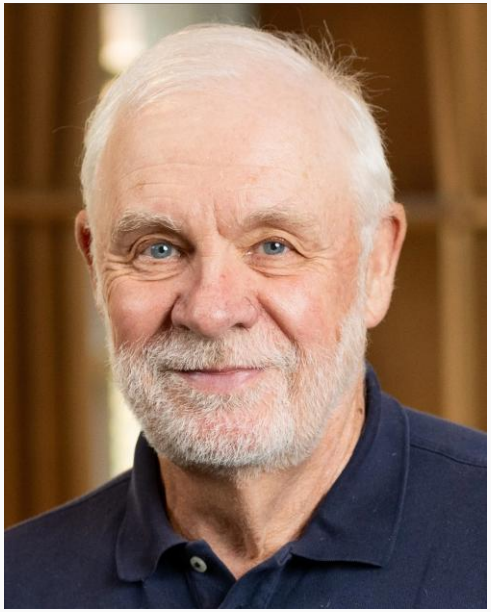
ADEMP-PreReg
Template for Simulation Studies

November 27, 2024

Deeper issues in simulation studies

Deeper issues in simulation studies



https://src.isr.umich.edu/research/faculty-profiles/profiles/littleroderick-j/

> Good simulation studies are not given the respect they deserve. Often the **design is perfunctory and simplistic** [...] and results are over-generalized.
>
> Roderick Little, 2013

Few constraints on plausible DGMs

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What is a useful/realistic data-generating mechanism?

Few constraints on plausible DGMs

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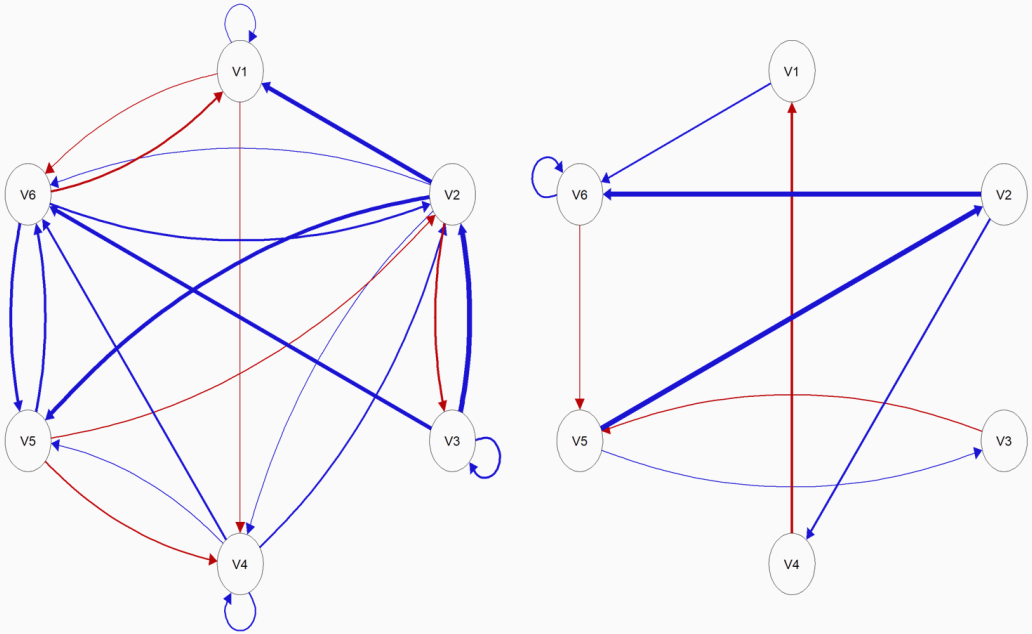

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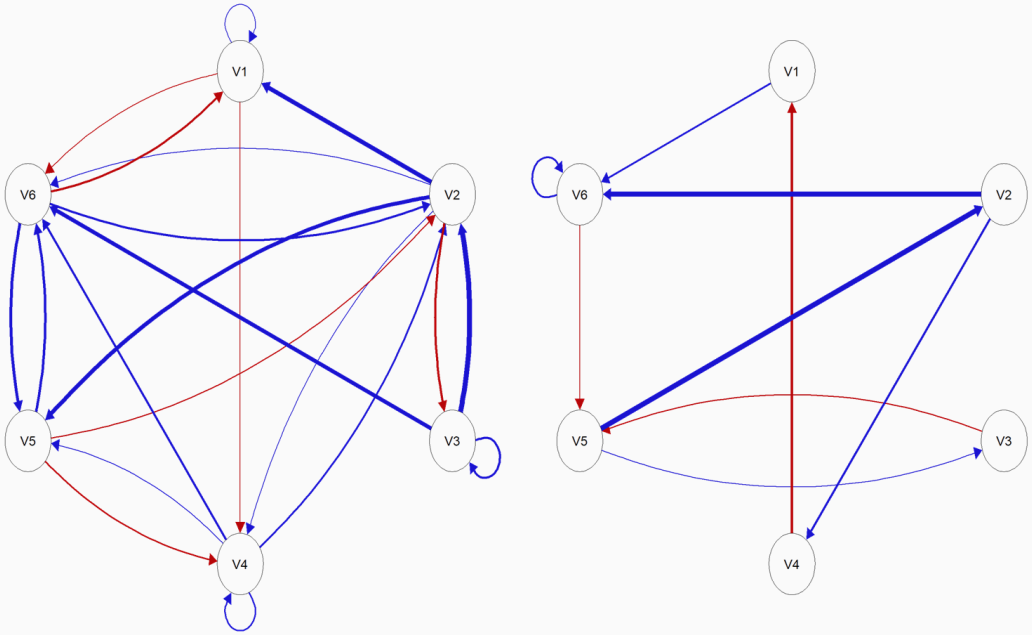
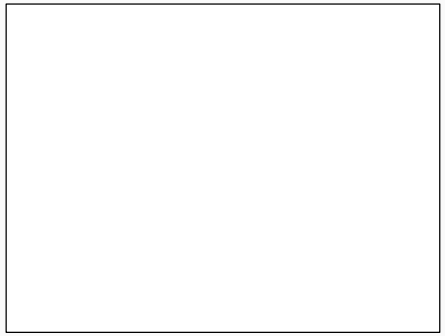


→ Hard to understand when performance differences actually matter

Part II: Solutions?

Exploring the data-generating space

Exploring the data-generating space



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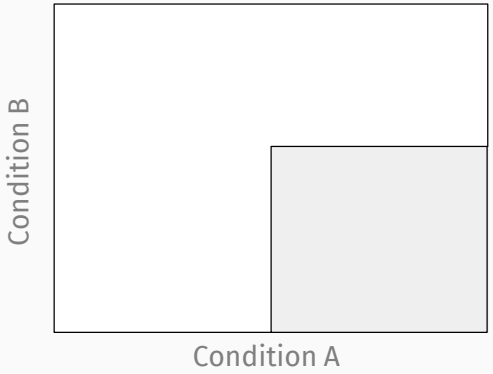

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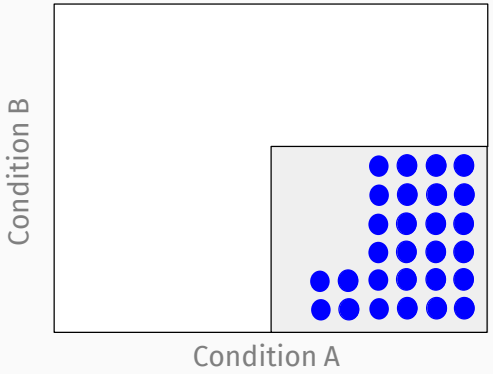

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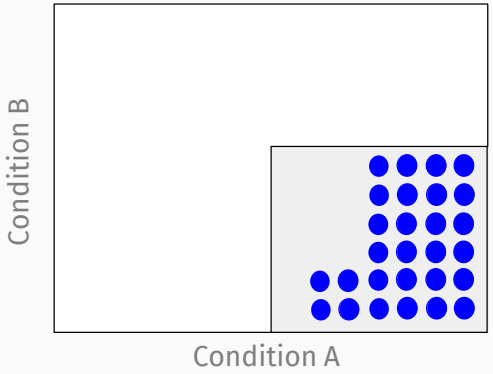

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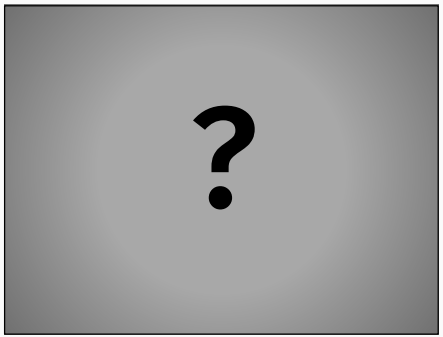

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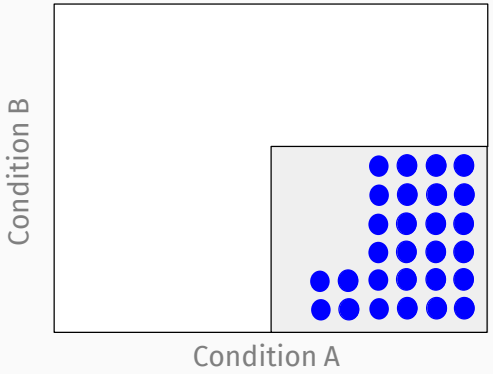

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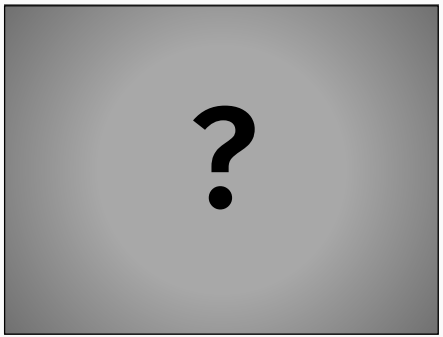
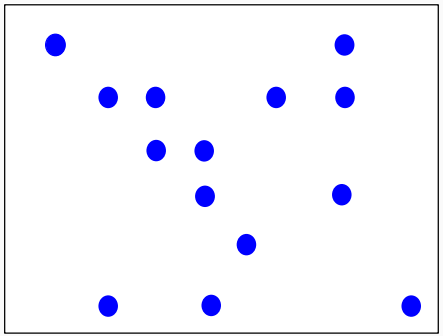


Efficient exploration



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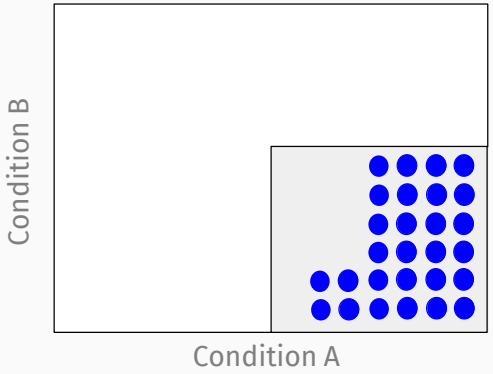

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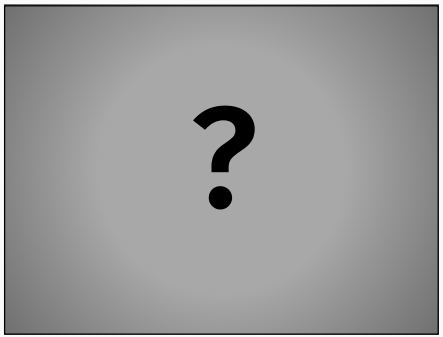

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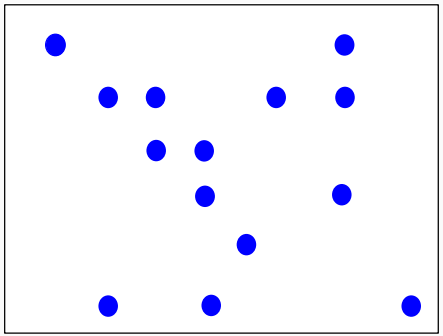
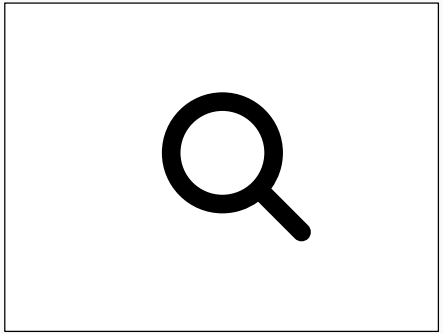
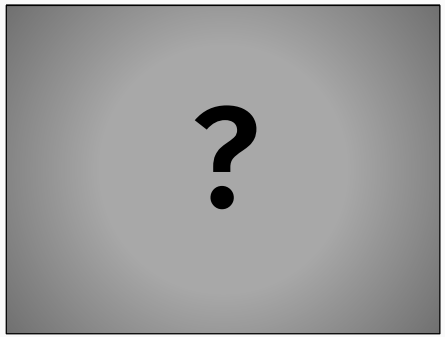


Benchmarking



The role of preregistration for transparency

Transparency



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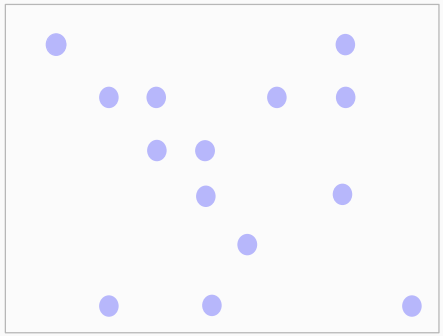

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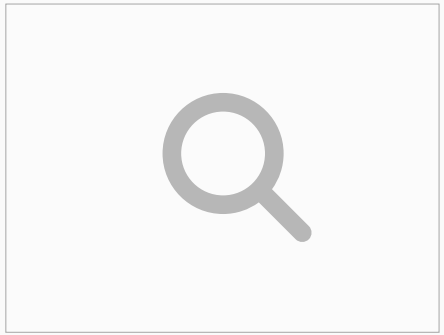

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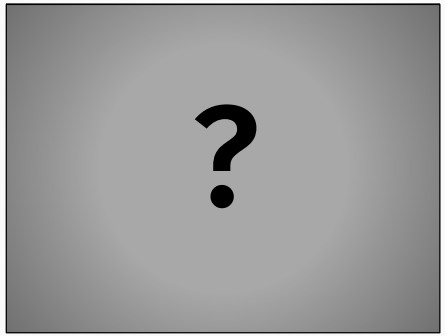

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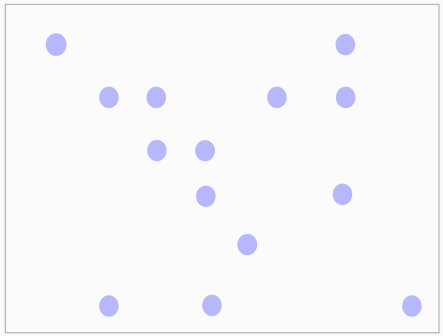

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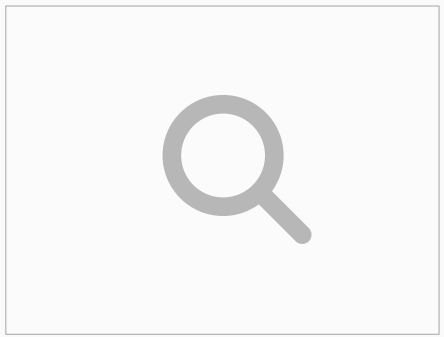

Why, when, and how to (or not to) preregister a simulation study

Björn S. Siepe[†] [1], František Bartoš [2*], Anne-Laure Boulesteix [3,4*], Daniel W. Heck [1*], Aaron Peikert [5,6*], Alexandra Sarafoglou [2*], Samuel Pawel [7]

Simulation studies make generalizable claims

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> **We recommend method XYZ for ordinal items**
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> Hypothetical authors

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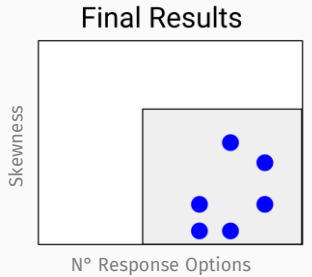
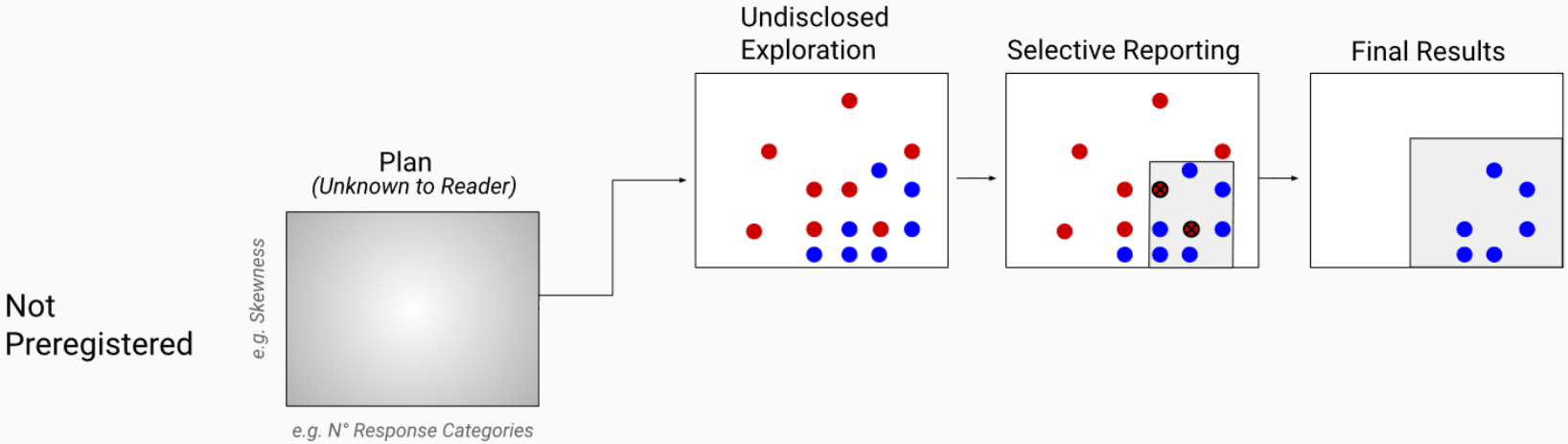


Preregistration reduces epistemic uncertainty



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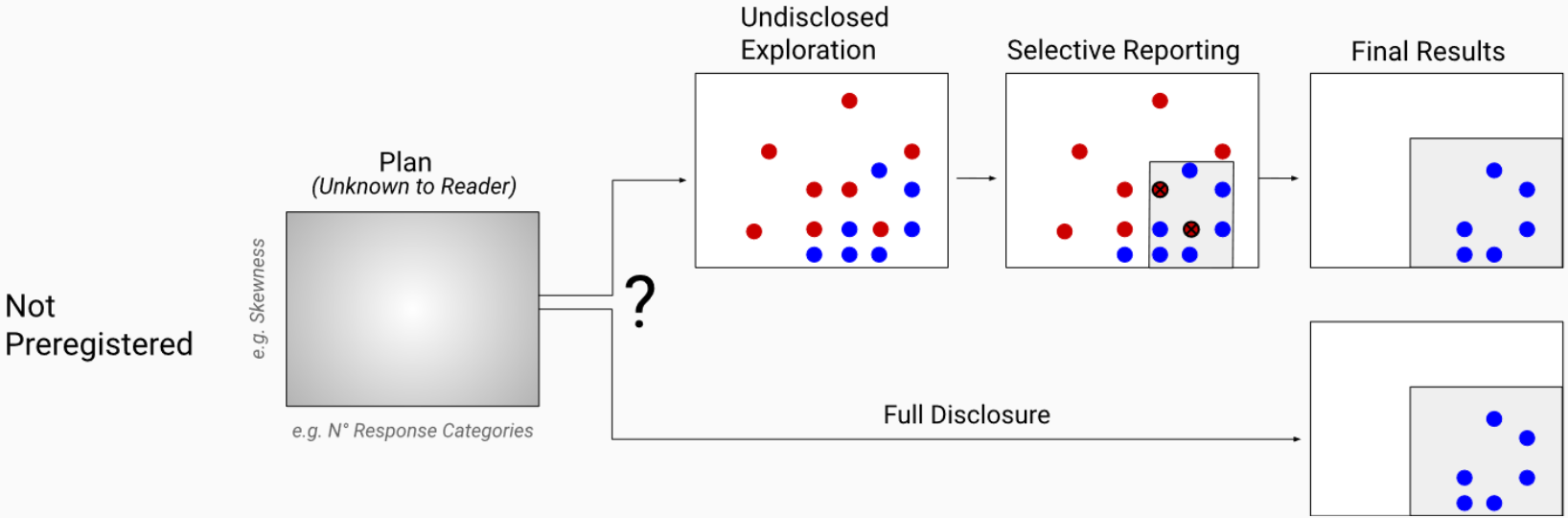

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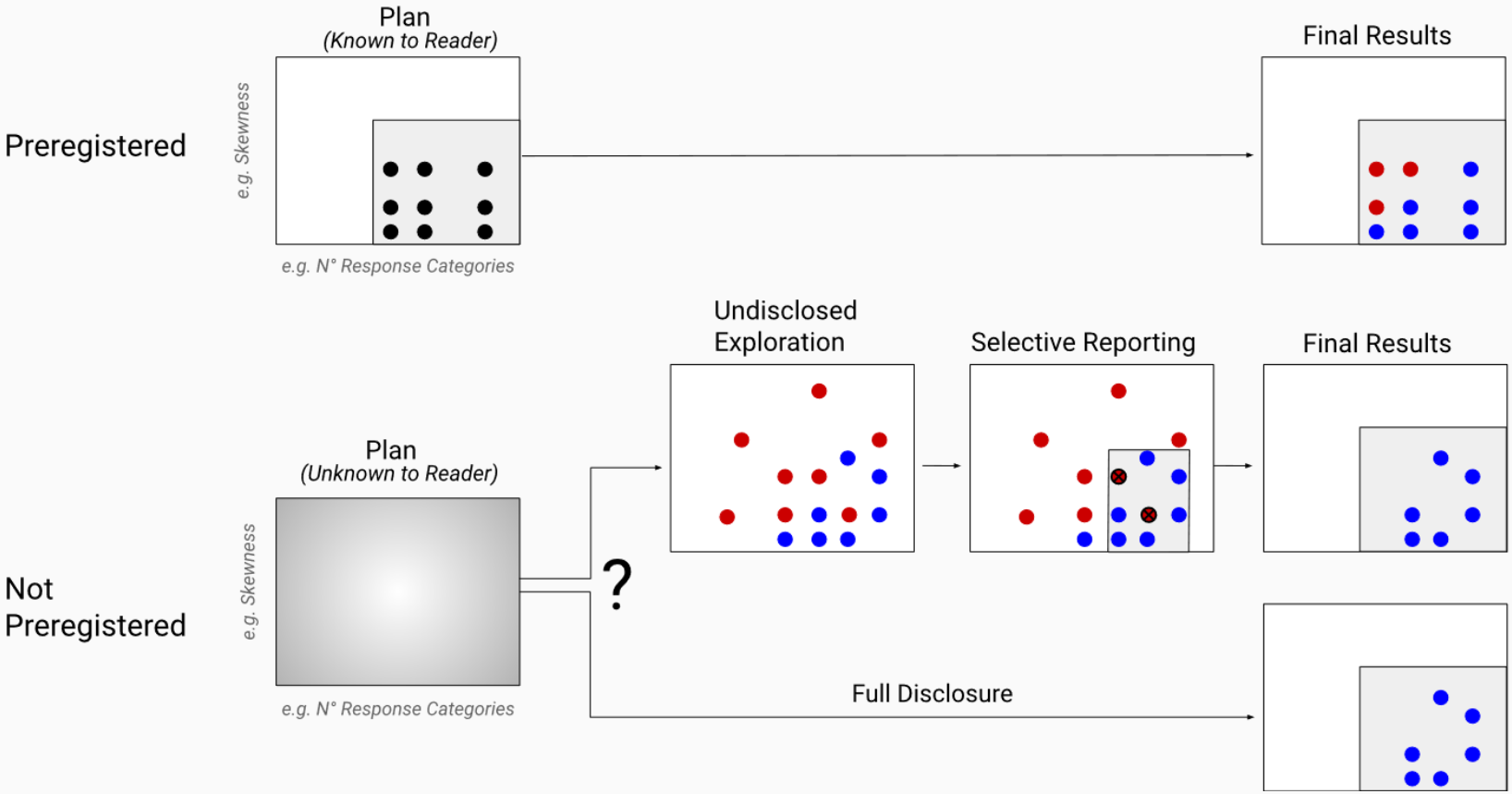

Registered Reports to the rescue

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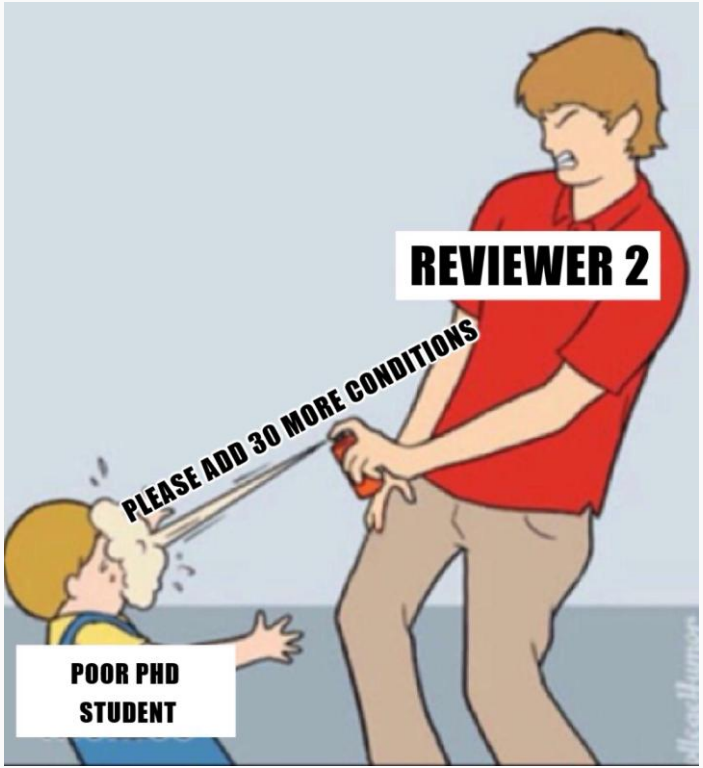

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Registered Reports to the rescue

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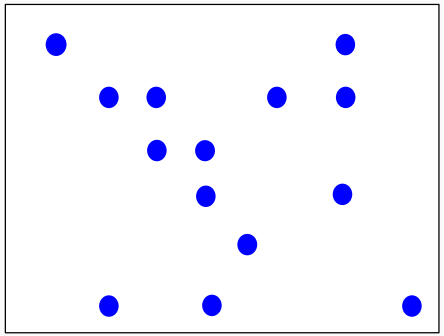
Centre for Open Science

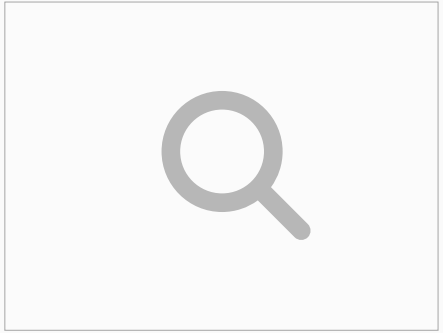
Exploring the data-generating space

Transparency

Efficient exploration



Benchmarking



Exploring more efficiently

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Multivariate Behavioral Research, *35* (2), 137-167

Design and Analysis of Monte Carlo Experiments:
Attacking the Conventional Wisdom

Anders Skrondal
Department of Epidemiology
National Institute of Public Health, Oslo

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Less but the same? Methods for Reducing the Size of Simulation Study Designs

Angelike & Papenberg (in prep.)

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Design of experiments for simulation studies: Comparing strategies using surrogate models

Hafiz, ..., & Peikert (in prep.)

Incentivizing cumulative simulation research

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Living Synthetic Benchmarks:
A Neutral and Cumulative Framework for Simulation Studies

František Bartoš [1], Samuel Pawel [2], Björn S. Siepe [3]

Incentivizing cumulative simulation research

Separate Studies (Status Quo)

Paper 1
(new method)

Living Synthetic Benchmarks: A Neutral and Cumulative Framework for Simulation Studies

František Bartoš [1], Samuel Pawel [2], Björn S. Siepe [3]

Incentivizing cumulative simulation research

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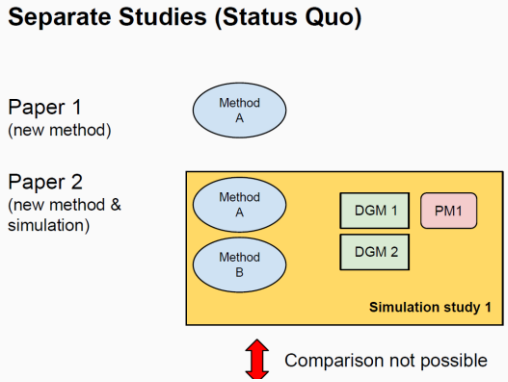

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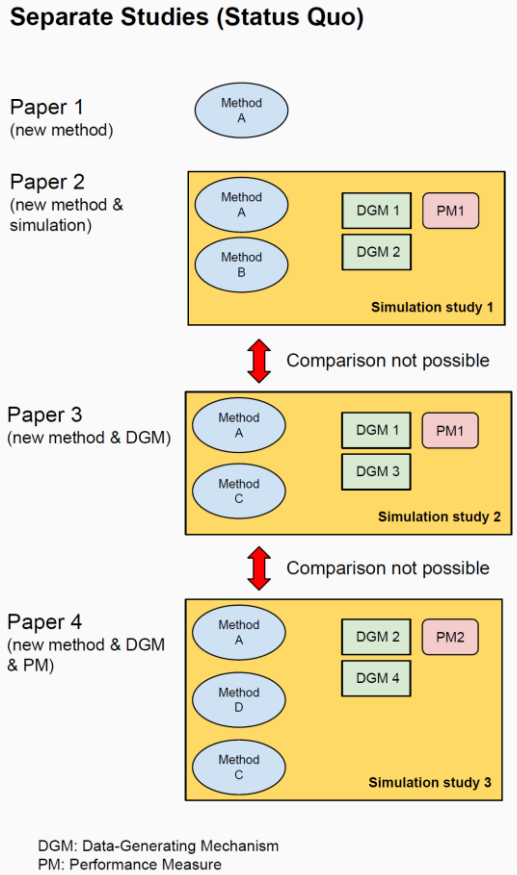

Exploring the data-generating space

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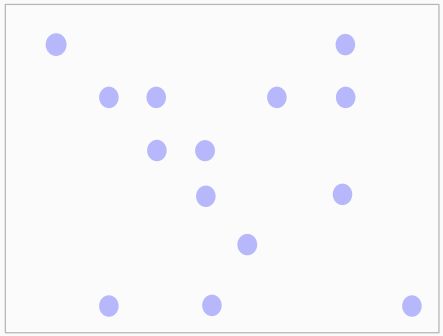
Transparency

Efficient exploration



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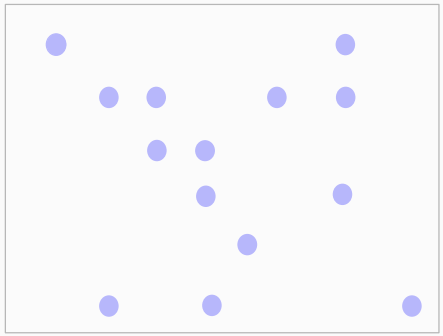
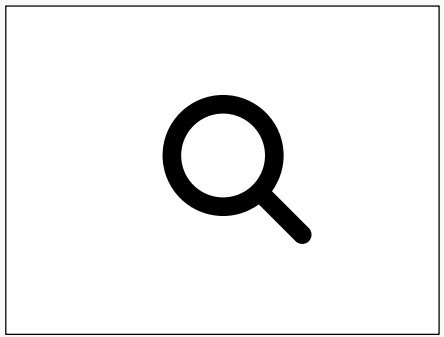


Benchmarking



What about *real* benchmarking?

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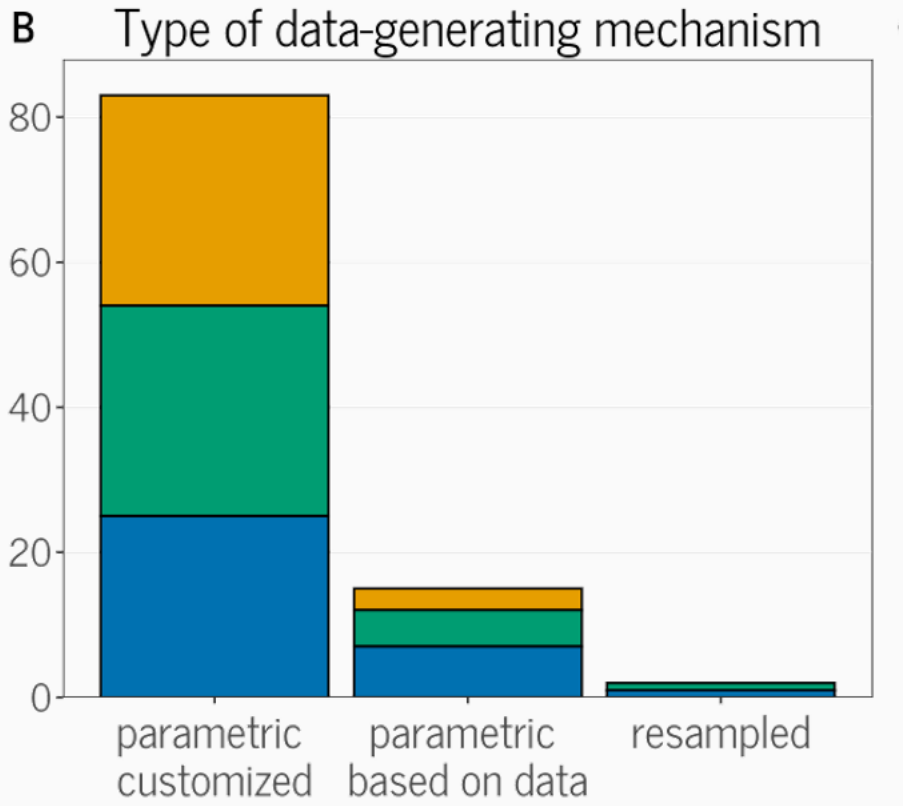

Psychology has been slow to adopt benchmarking

Psychology has been slow to adopt benchmarking

Computer Vision/ML

Source: Steni Sebastian, Medium

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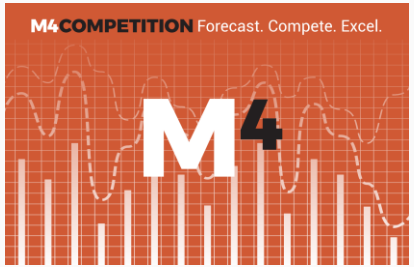
Forecasting



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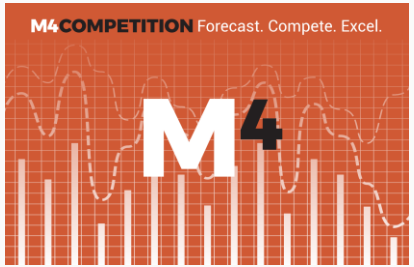

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Biostatistics

Robinson and Vitek *Genome Biology* (2019) 20:205
https://doi.org/10.1186/s13059-019-1846-5

EDITORIAL

Benchmarking comes of age

Mark D. Robinson[1*] and Olga Vitek[2*]

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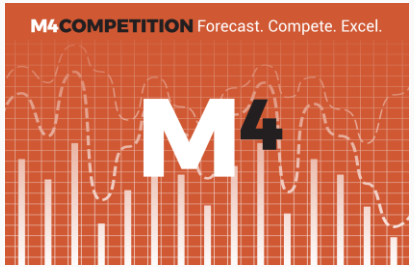

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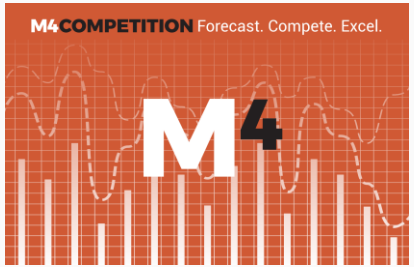

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1. Lack of openly available data
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The time is ripe for benchmarking

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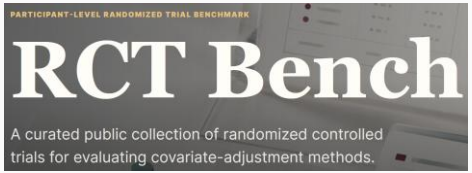
We now have lots of open data

Item Response Warehouse



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We now have lots of open data + **Some of us care about prediction**

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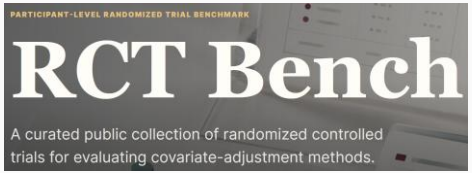

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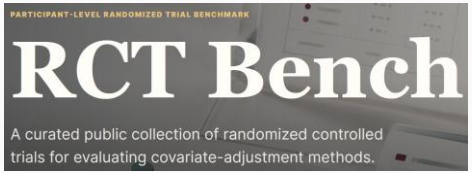

Perspectives on Psychological Science
Volume 12, Issue 6, November 2017, Pages 1100-1122

https://doi.org/10.1177/1745691617693393

SAGE journals

Choosing Prediction Over Explanation in Psychology: Lessons From Machine Learning

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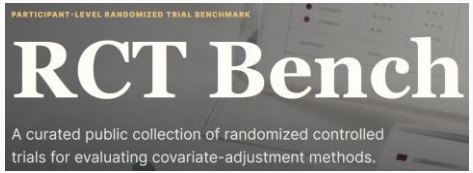

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Benchmarking and simulations

Benchmarking

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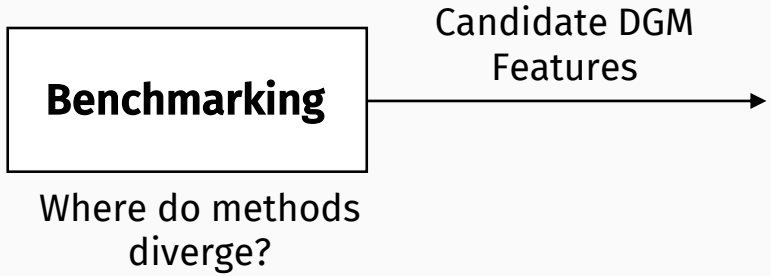

Benchmarking and simulations

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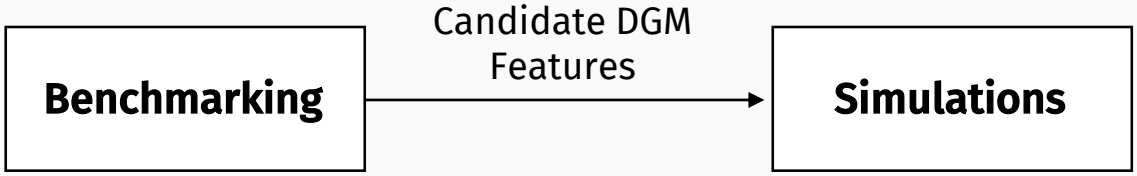


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On the role of benchmarking data sets and simulations in method comparison studies

Sarah Friedrich, Tim Friede

First published: 21 February 2023 | https://doi.org/10.1002/bimj.202200212 | VIEW METRICS

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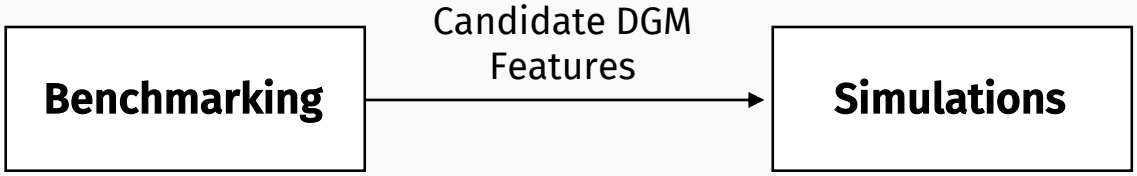

Where do methods diverge?

Which aspects drive differences?

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Statistical Parametric Simulation Studies Based on Real Data

Christina Sauer, F. Julian D. Lange, Maria Thurow, Ina Dormuth, Anne-Laure Boulesteix

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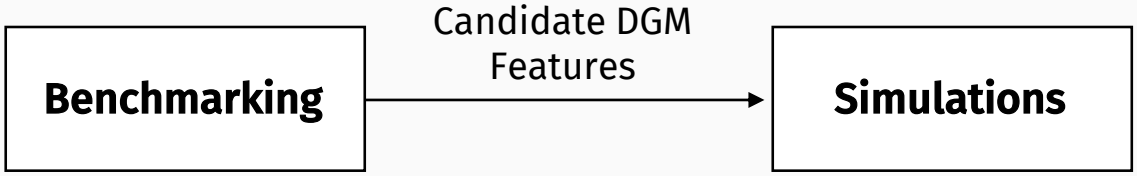

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Weber *et al. Genome Biology* (2019) 20:125
https://doi.org/10.1186/s13059-019-1738-8

Genome Biology

REVIEW Open Access

Essential guidelines for computational method benchmarking

Check for updates

Lukas M. Weber[1,2], Wouter Saelens[3,4], Robrecht Cannoodt[3,4], Charlotte Soneson[1,2,8], Alexander Hapfelmeier[5], Paul P. Gardner[6], Anne-Laure Boulesteix[7], Yvan Saeys[3,4*] and Mark D. Robinson[1,2*]

Simulations, 51 years later

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> **Statisticians ... often pay too little attention to their own principles of design**
>
> Hoaglin & Andrews, 1975

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The field is moving fast:

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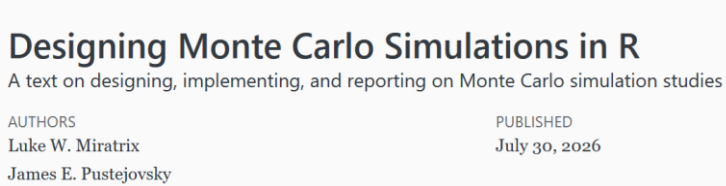

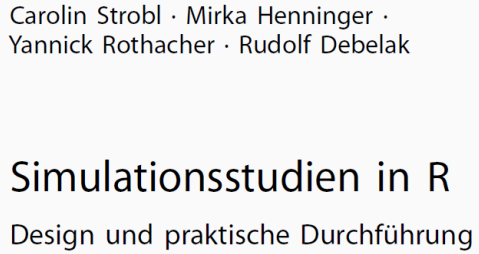

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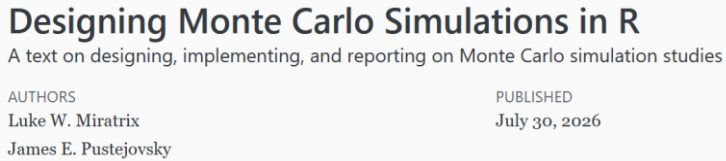

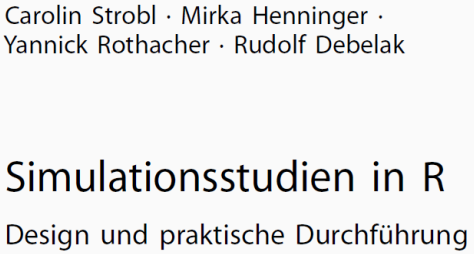

Adopt Registered Reports at Psychological Methods

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EDITORIAL | Free Access

Editorial for the special collection "Towards neutral comparison studies in methodological research"

Anne-Laure Boulesteix, Mark Baillie, Dominic Edelmann, Leonhard Held, Tim P. Morris, Willi Sauerbrei

First published: 17 February 2024 | https://doi.org/10.1002/bimj.202400031 | VIEW METRICS

Designing Monte Carlo Simulations in R

A text on designing, implementing, and reporting on Monte Carlo simulation studies

AUTHORS
Luke W. Miratrix
James E. Pustejovsky

PUBLISHED
July 30, 2026

Carolin Strobl · Mirka Henninger · Yannick Rothacher · Rudolf Debelak

Simulationsstudien in R

Design und praktische Durchführung

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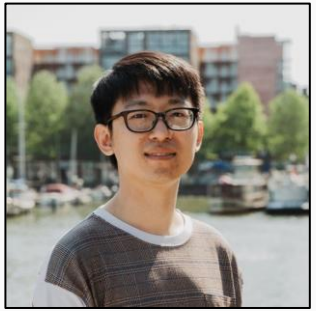
Co-Authors





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Slides & Papers

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Resources