Bayesianizmus a gyakorlatban

ACZÉL BALÁZS

ELTE Pszichológiai Intézet

Metatudomány Kutatócsoport

NHST

$$p < .05$$

FONTOS KÉRDÉSEK

- Mit tudunk meg a H1 igaz voltáról?
- Ha elvetjük, akkor mennyire lehetünk biztosak, hogy igaz a hipotézisünk?
- Ha nem vetjük el, akkor mit tudtunk meg?
- Mikor érvelhetünk a null mellett?

A BF elemzés előnyei

- Az evidencia erősségéről tudósít
- A nullhipotézisről is informál
- Szekvenciális mintavétel lehetséges
- Tervezett vs post hoc összehasonlítások nem okoznak gondod

Bayes factor evidence categories	Value of the Bayes factor
Strong support for H1	> 10
Moderate support for H1	3–10
Anecdotal support for H1	1–3
Equal support for the hypotheses	1
Anecdotal support for H0	1/3–1
Moderate support for H0	1/10–1/3
Strong support for H0	< 1/10

Milyen erősek a pszichológiai eredmények?

Aczel, B., Palfi, B., & Szaszi, B. (2017). Estimating the evidential value of significant results in psychological science. *PLoS One*, *12*(8), e0182651.

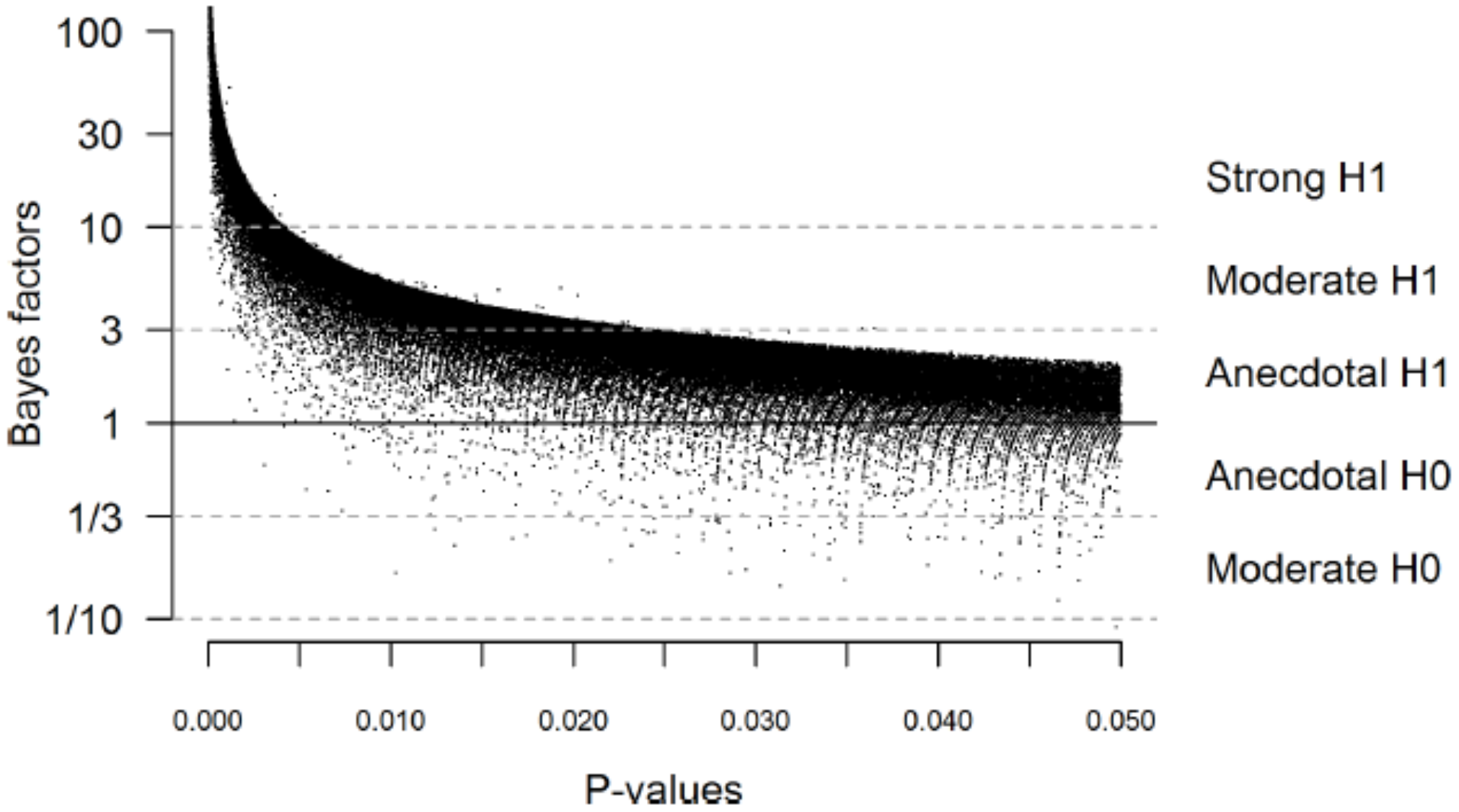
1985-2016

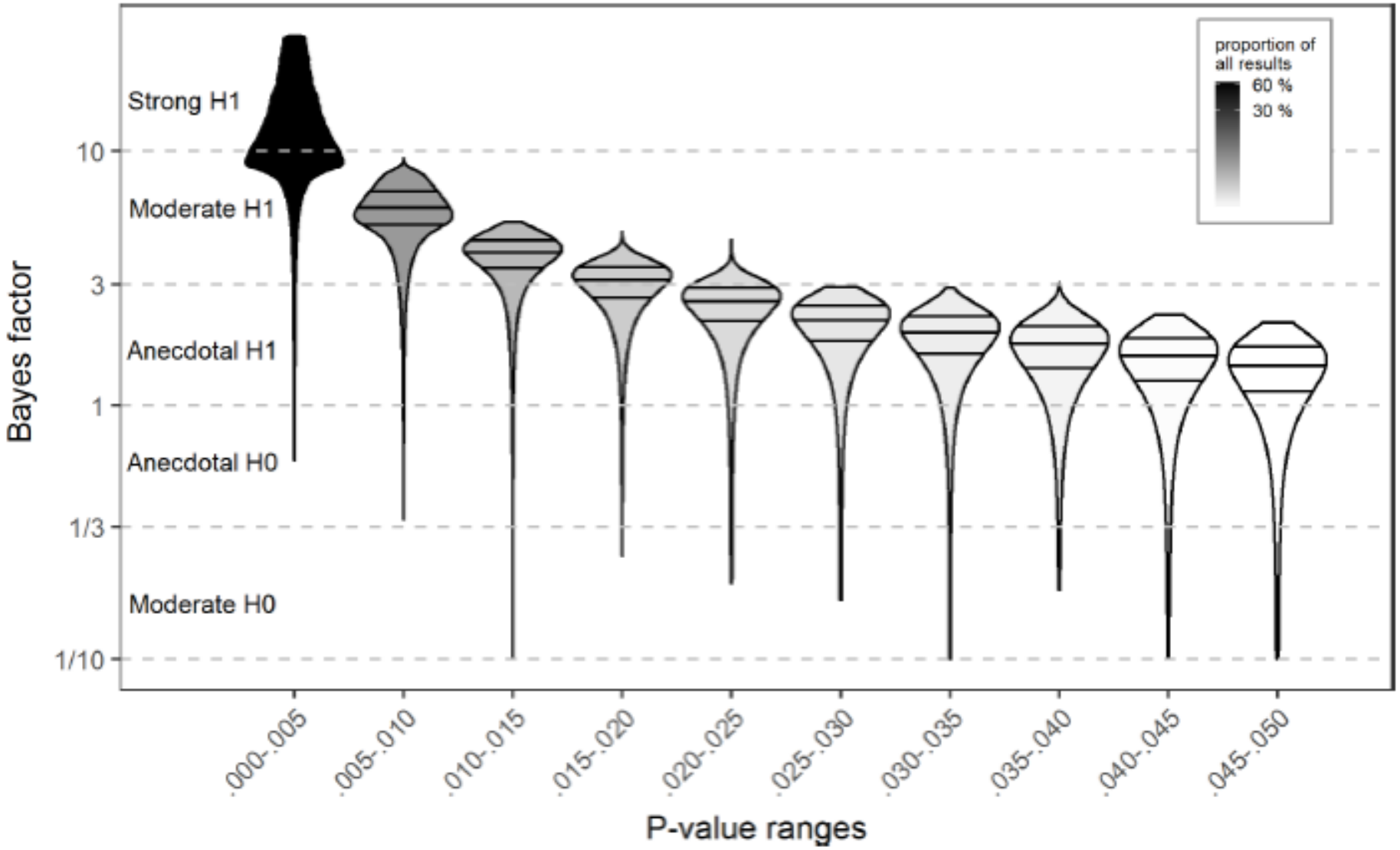
293 pszichológiai folyóirat

35515 cikk

287424 statisztikai eredmény

Hartgerink CH. 688,112 Statistical Results: Content Mining Psychology Articles for Statistical Test Results. Data. 2016; 1(3):14.

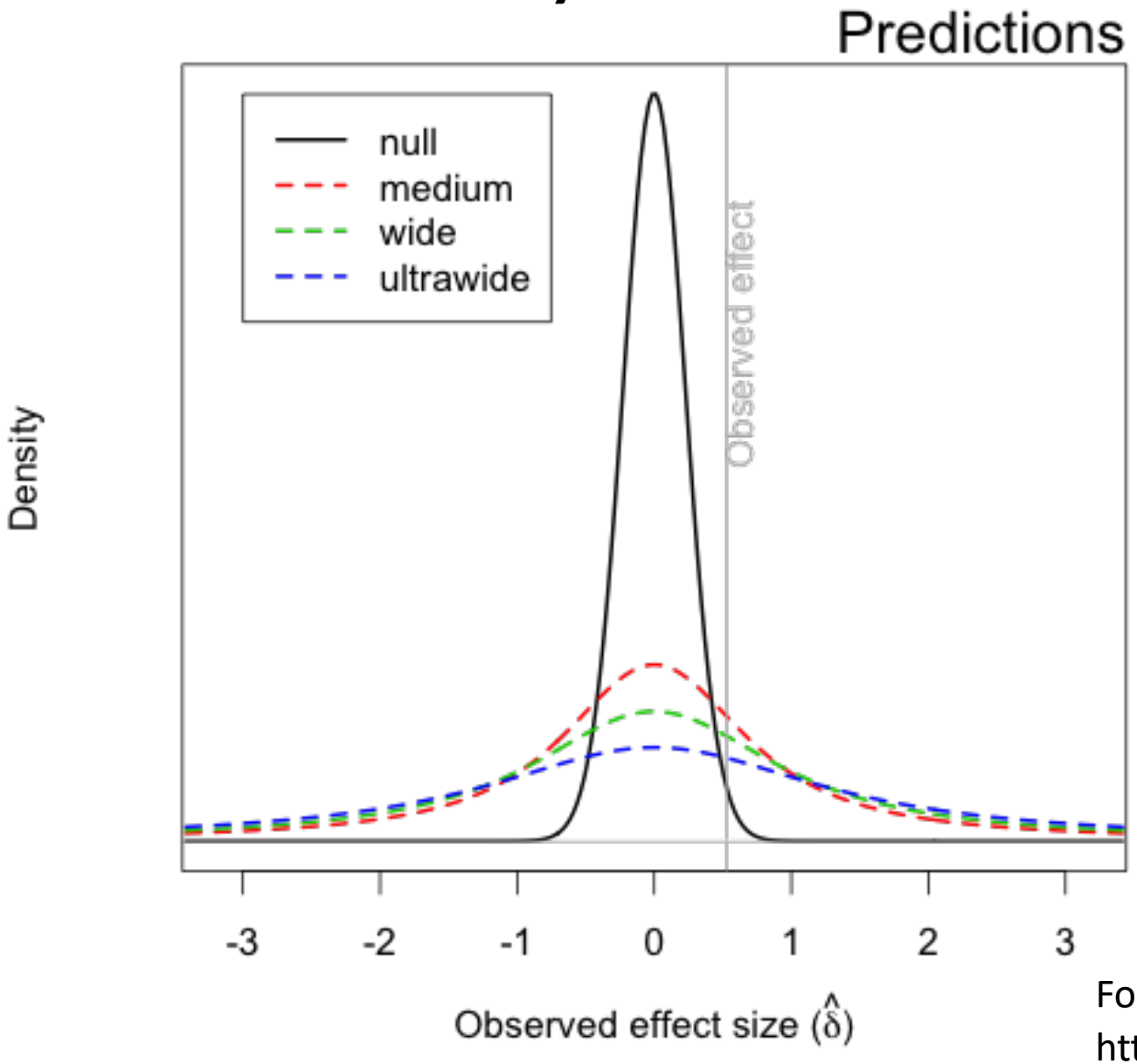

100
30
10
3
1
1/3
1/10
Bayes factors
0.000
0.010
0.020
0.030
0.040
0.050
P-values
Strong H1
Moderate H1
Anecdotal H1
Anecdotal H0
Moderate H0


proportion of all results
60 %
30 %
Strong H1
Moderate H1
Anecdotal H1
Anecdotal H0
Moderate H0
10
3
1
1/3
1/10
Bayes factor
.000-.005
.005-.010
.010-.015
.015-.020
.020-.025
.025-.030
.030-.035
.035-.040
.040-.045
.045-.050
P-value ranges

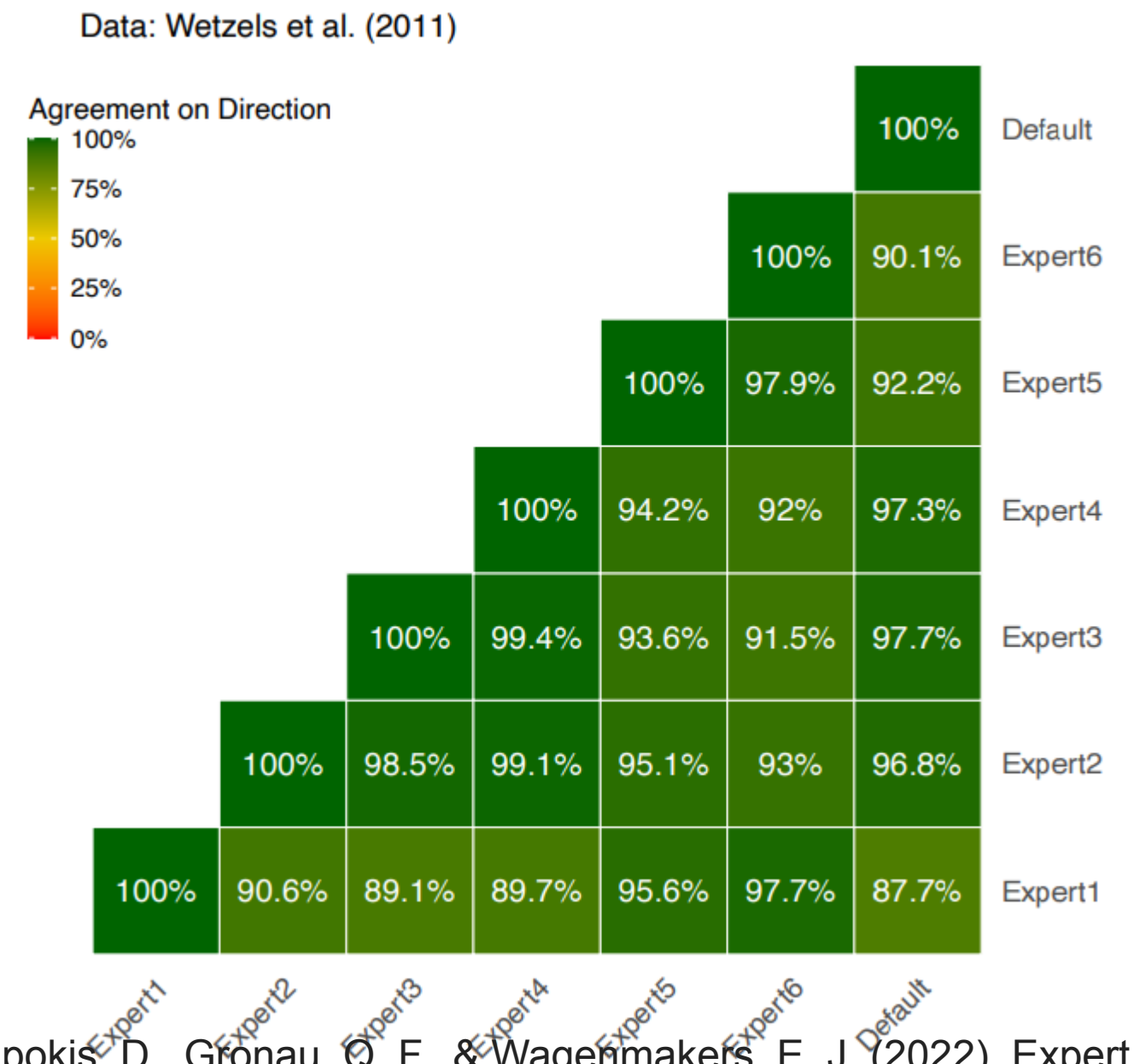
Milyen erősek a nem-szignifikáns pszichológiai eredmények?

Aczel, B., Palfi, B., Szollosi, A., Kovacs, M., Szaszi, B., Szecsi, P., ... & Wagenmakers, E. J. (2018). Quantifying support for the null hypothesis in psychology: An empirical investigation. *Advances in Methods and Practices in Psychological Science*, *1*(3), 357-366.

Bayes Faktor



Forrás:
http://bayesfactor.blogspot.hu



Stefan, A. M., Katsimpokis, D., Gronau, Q. F., & Wagenmakers, E. J. (2022). Expert agreement in prior elicitation and its effects on Bayesian inference. *Psychonomic Bulletin & Review*, 1-19.

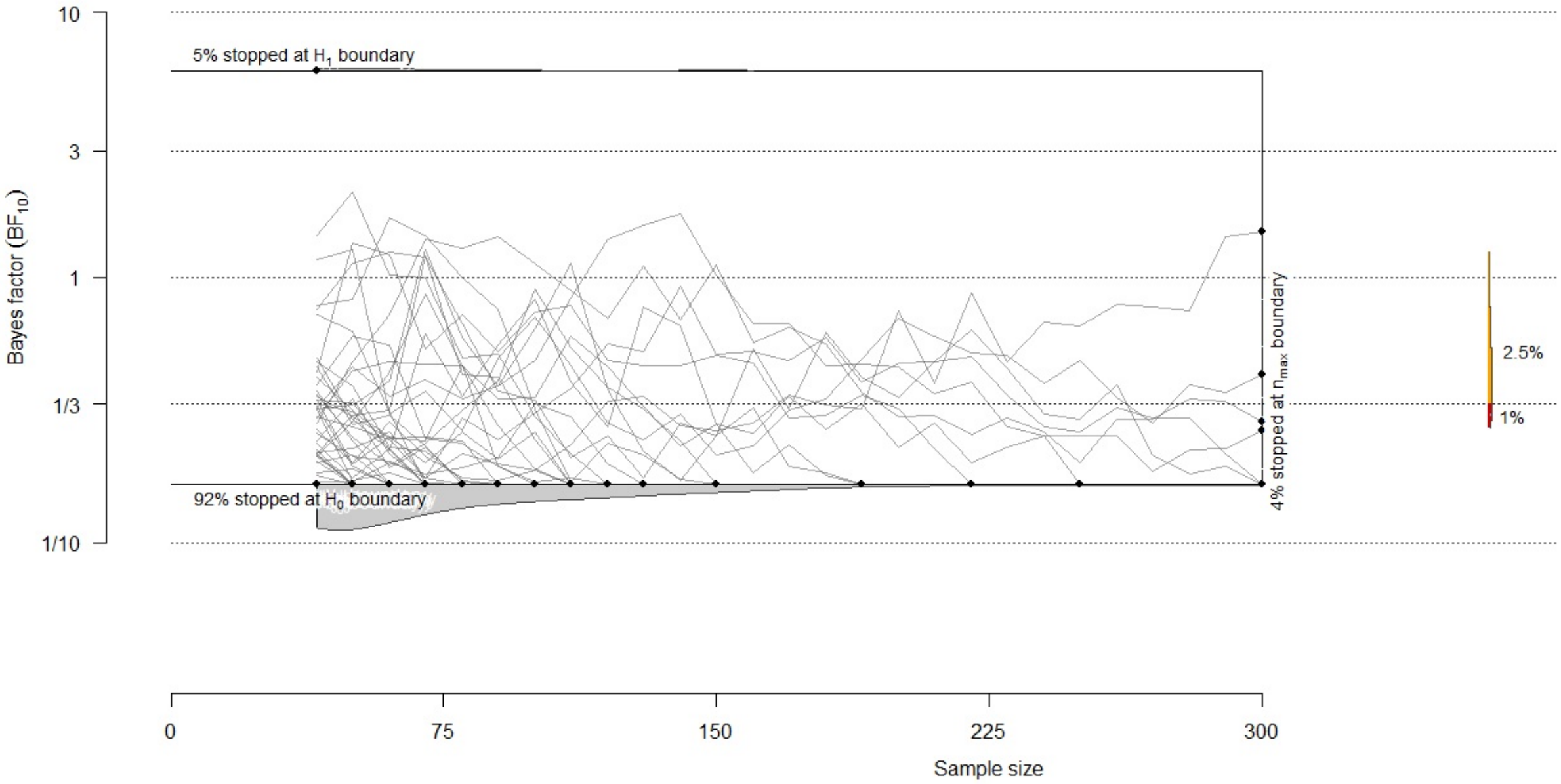
Psychon Bull Rev (2018) 25:128–142
DOI 10.3758/s13423-017-1230-y

BRIEF REPORT

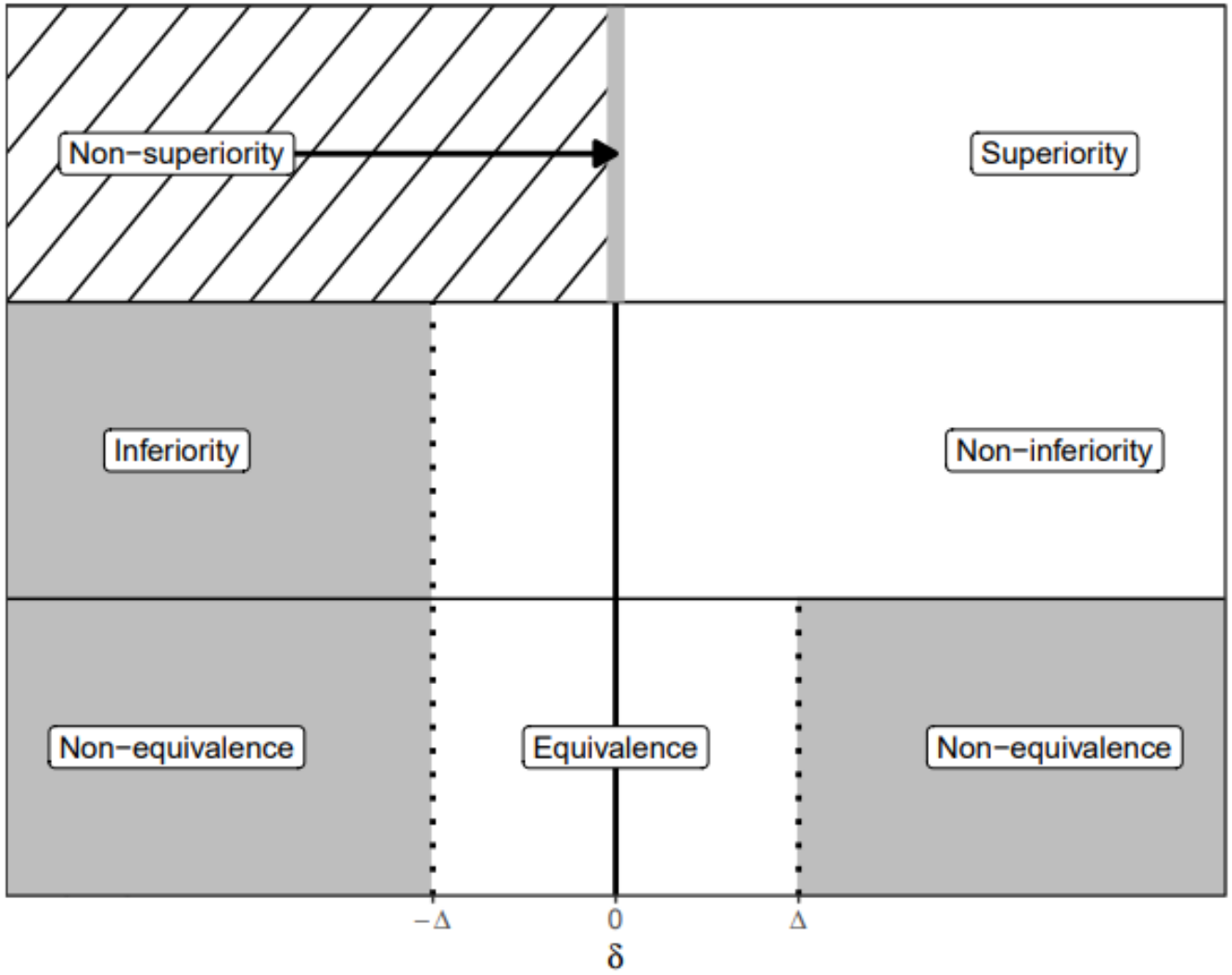
Bayes factor design analysis: Planning for compelling evidence

Felix D. Schönbrodt[1] · Eric-Jan Wagenmakers[2]

Szekvenciális mintavétel

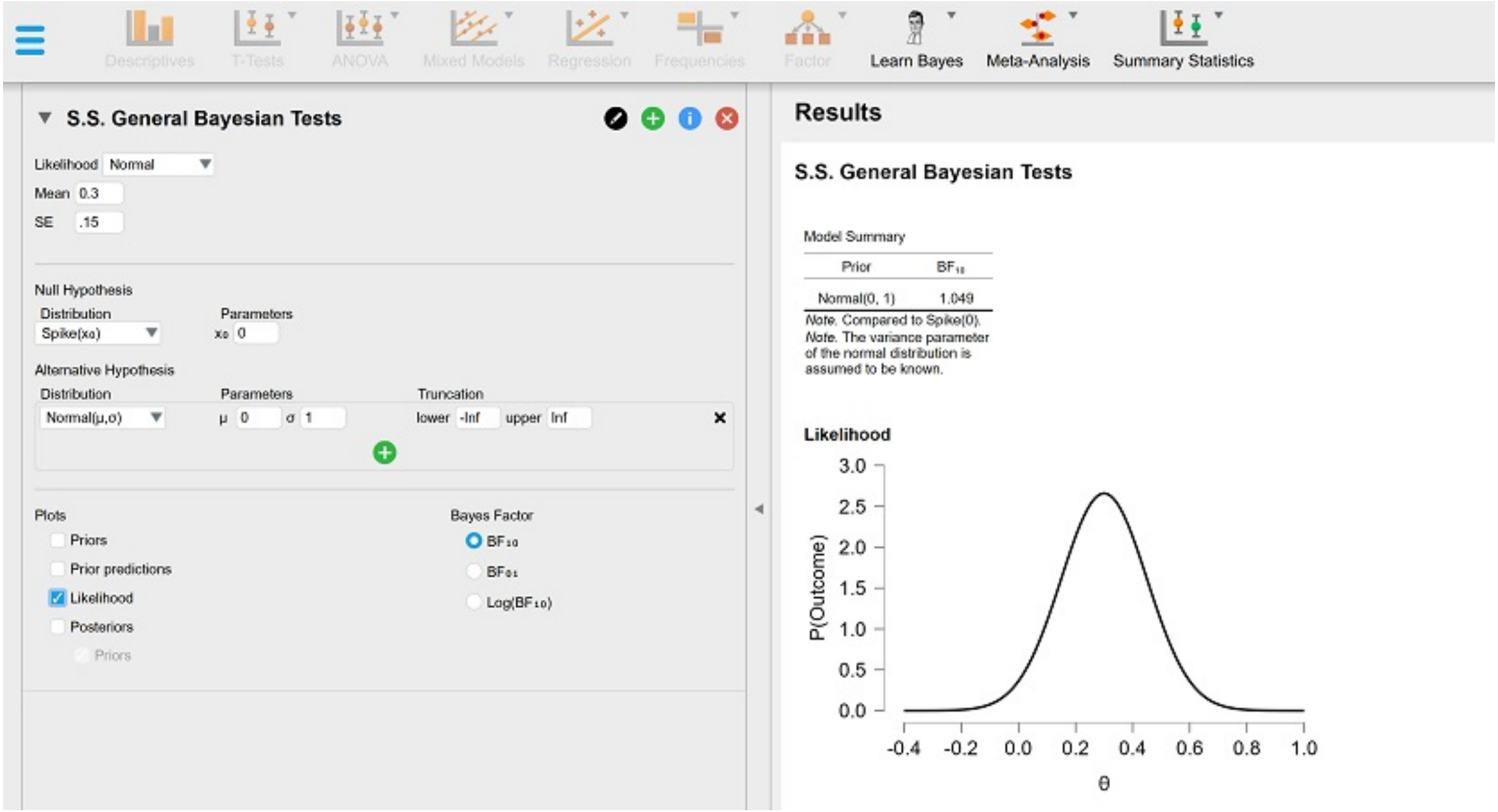


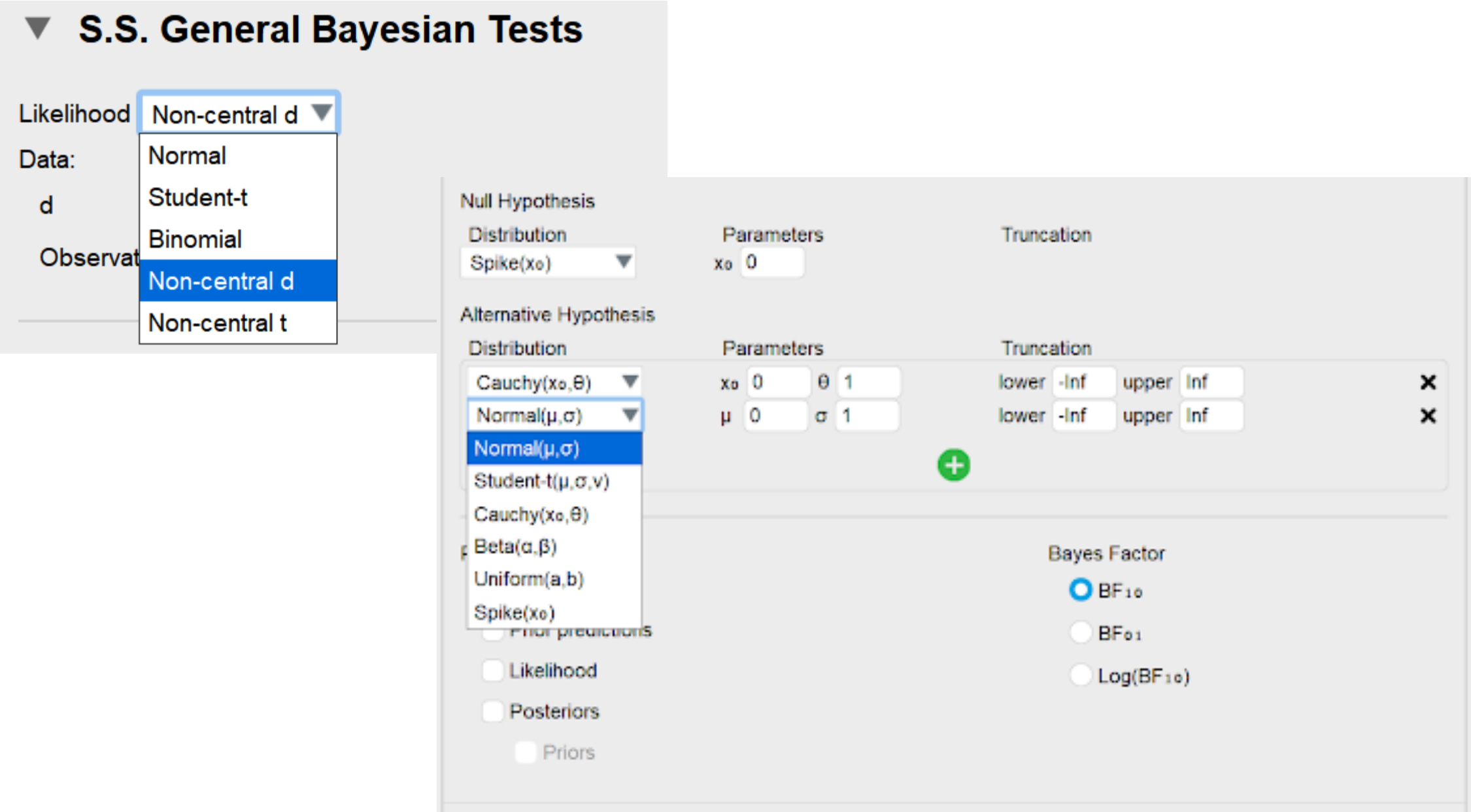
Schematic Depiction of the Superiority, Non-Inferiority, and Equivalence Designs.

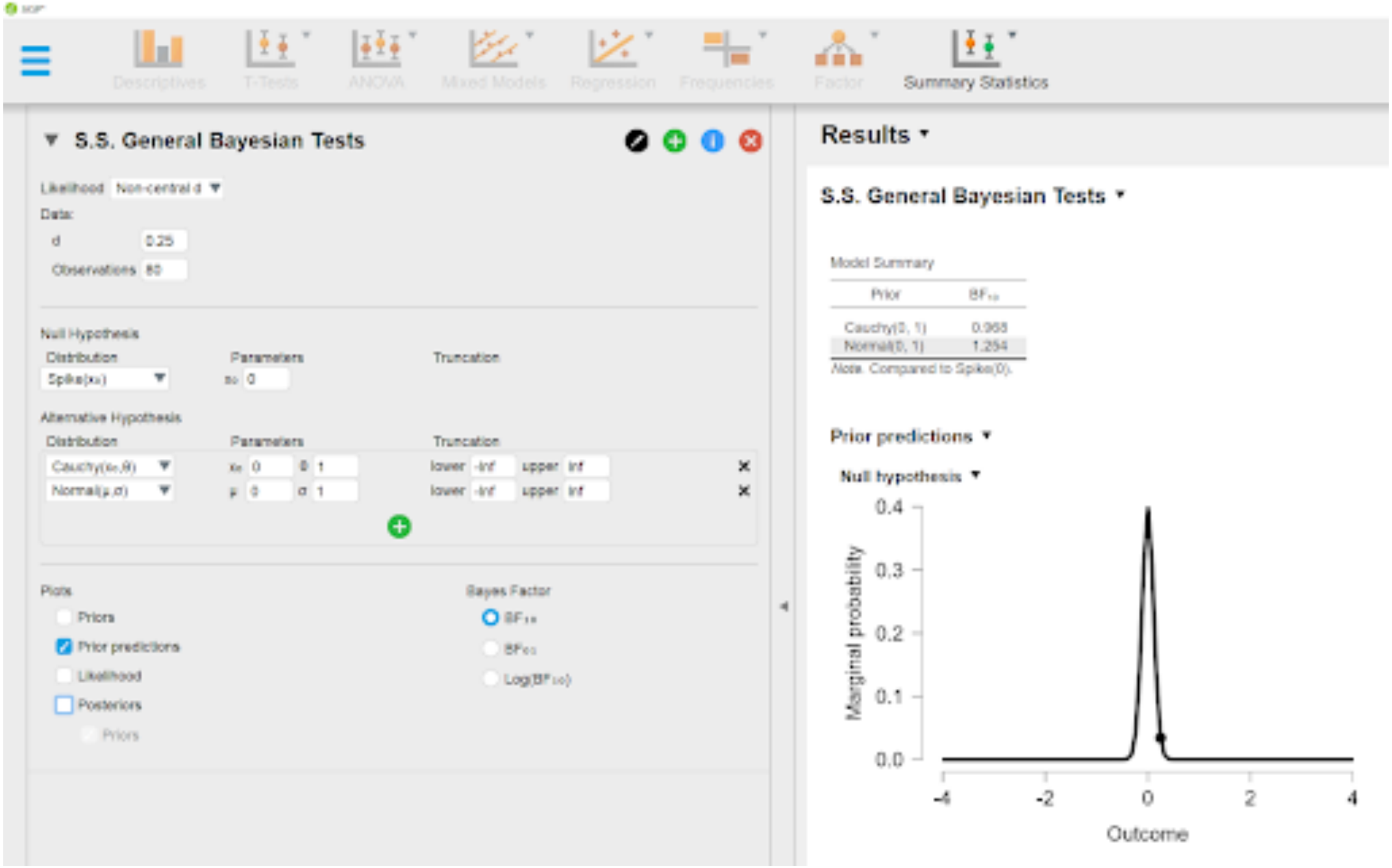


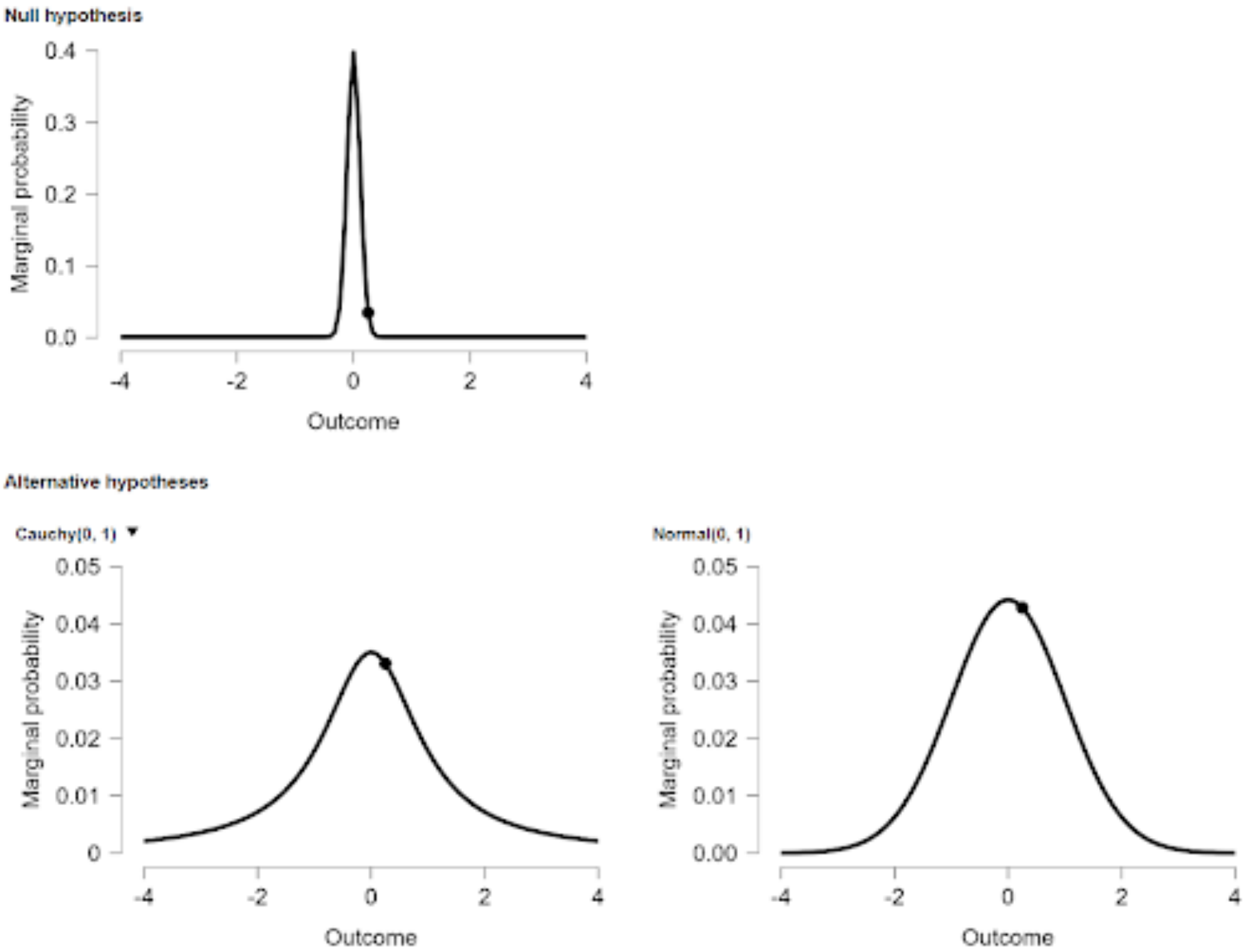
Heck, D. W., Boehm, U., Böing-Messing, F., Bürkner, P., Derks, K., Dienes, Z., Fu, Q., Gu, X., Karimova, D., Kiers, H., Klugkist, I., Kuiper, R. M., Lee, M. D., Leenders, R., Leplaa, H. J., Linde, M., Ly, A., Meijerink, M., Moerbeek, M., ... Hoijtink, H. (2022). A review of applications of the Bayes factor in psychological research. *Psychological Methods*.

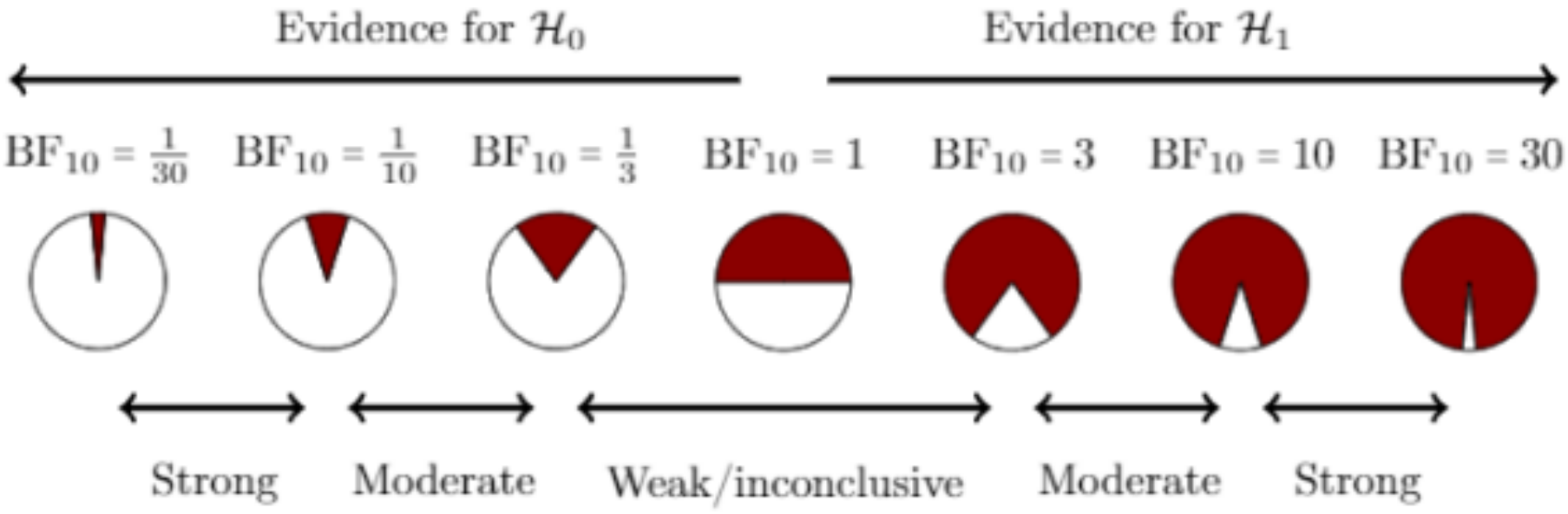
JASP


Descriptives
T-Tests
ANOVA
Mixed Models
Regression
Frequencies
Factor
Learn Bayes
Meta-Analysis
Summary Statistics
S.S. General Bayesian Tests
Likelihood Normal
Mean 0.3
SE .15
Null Hypothesis
Distribution
Parameters
Spike(x0)
x0 0
Alternative Hypothesis
Distribution
Parameters
Truncation
Normal(μ,σ)
μ 0
σ 1
lower -Inf
upper Inf
Plots
Priors
Prior predictions
Likelihood
Posteriors
Priors
Bayes Factor
BF10
BF01
Log(BF10)
Results
S.S. General Bayesian Tests
Model Summary
Prior
BF10
Normal(0, 1)
1.049
Note. Compared to Spike(0).
Note. The variance parameter of the normal distribution is assumed to be known.
Likelihood
P(Outcome)
3.0
2.5
2.0
1.5
1.0
0.5
0.0
-0.4
-0.2
0.0
0.2
0.4
0.6
0.8
1.0
θ

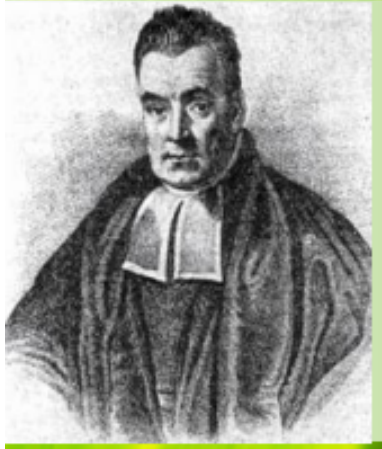

S.S. General Bayesian Tests
Likelihood
Non-central d
Data:
d
Observat
Normal
Student-t
Binomial
Non-central d
Non-central t
Null Hypothesis
Distribution
Parameters
Truncation
Spike(x₀)
x₀ 0
Alternative Hypothesis
Distribution
Parameters
Truncation
Cauchy(x₀,θ)
x₀ 0 θ 1
lower -Inf upper Inf
Normal(μ,σ)
μ 0 σ 1
lower -Inf upper Inf
Normal(μ,σ)
Student-t(μ,σ,ν)
Cauchy(x₀,θ)
Beta(α,β)
Uniform(a,b)
Spike(x₀)
Likelihood
Posteriors
Priors
Bayes Factor
BF₁₀
BF₀₁
Log(BF₁₀)


Descriptives
T-Tests
ANOVA
Mixed Models
Regression
Frequencies
Factor
Summary Statistics
S.S. General Bayesian Tests
Likelihood
Non-central d
Data:
d
0.25
Observations
80
Null Hypothesis
Distribution
Parameters
Truncation
Spike(x₀)
x₀ 0
Alternative Hypothesis
Distribution
Parameters
Truncation
Cauchy(x₀,θ)
x₀ 0
θ 1
lower -Inf
upper Inf
Normal(μ,σ)
μ 0
σ 1
lower -Inf
upper Inf
Plots
Priors
Prior predictions
Likelihood
Posteriors
Priors
Bayes Factor
BF₁₀
BF₀₁
Log(BF₁₀)
Results
S.S. General Bayesian Tests
Model Summary
Prior
BF₁₀
Cauchy(0, 1)
0.968
Normal(0, 1)
1.254
Note. Compared to Spike(0).
Prior predictions
Null hypothesis
Marginal probability
0.4
0.3
0.2
0.1
0.0
-4
-2
0
2
4
Outcome


Null hypothesis
Marginal probability
0.4
0.3
0.2
0.1
0.0
-4
-2
0
2
4
Outcome
Alternative hypotheses
Cauchy(0, 1)
Marginal probability
0.05
0.04
0.03
0.02
0.01
0
-4
-2
0
2
4
Outcome
Normal(0, 1)
Marginal probability
0.05
0.04
0.03
0.02
0.01
0.00
-4
-2
0
2
4
Outcome


Evidence for $\mathcal{H}_0$
Evidence for $\mathcal{H}_1$
$BF_{10} = \frac{1}{30}$
$BF_{10} = \frac{1}{10}$
$BF_{10} = \frac{1}{3}$
$BF_{10} = 1$
$BF_{10} = 3$
$BF_{10} = 10$
$BF_{10} = 30$
Strong
Moderate
Weak/inconclusive
Moderate
Strong

JASP



BAYESIAN INFERENCE IN JASP:

A GUIDE FOR STUDENTS

http://static.jasp-stats.org/Manuals/Bayesian_Guide_v0.12.2.pdf

Bayes és R

van de Schoot, R., Winter, S. D., Ryan, O., Zondervan-Zwijnenburg, M., & Depaoli, S. (2017). A systematic review of Bayesian articles in psychology: The last 25 years. *Psychological Methods*, *22*(2), 217.

frontiers in
PSYCHOLOGY

METHODS ARTICLE
published: 29 July 2014
doi: 10.3389/fpsyg.2014.00781

Using Bayes to get the most out of non-significant results

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Psychon Bull Rev (2014) 21:301–308
DOI 10.3758/s13423-014-0595-4

Optional stopping: No problem for Bayesians

Jeffrey N. Rouder

Psychon Bull Rev
DOI 10.3758/s13423-017-1323-7

BRIEF REPORT

Bayesian inference for psychology. Part II: Example applications with JASP

Eric-Jan Wagenmakers[1] · Jonathon Love[1] · Maarten Marsman[1] · Tahira Jamil[1] · Alexander Ly[1] · Josine Verhagen[1] · Ravi Selker[1] · Quentin F. Gronau[1] · Damian Dropmann[1] · Bruno Boutin[1] · Frans Meerhoff[1] · Patrick Knight[1] · Akash Raj[2] · Erik-Jan van Kesteren[1] · Johnny van Doorn[1] · Martin Šmíra[3] · Sacha Epskamp[1] · Alexander Etz[4] · Dora Matzke[1] · Tim de Jong[1] · Don van den Bergh[1] · Alexandra Sarafoglou[1] · Helen Steingroever[1] · Koen Derks[1] · Jeffrey N. Rouder[5] · Richard D. Morey[6]

Reference as: Etz, A., Gronau, Q. F., Dablander, F., Edelsbrunner, P. A., Baribault, B. (in press). How to become a Bayesian in eight easy steps: An annotated reading list. *Psychonomic Bulletin & Review*.

How to become a Bayesian in eight easy steps: An annotated reading list

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University of California, Irvine

Quentin F. Gronau
University of Amsterdam

Fabian Dablander
University of Tübingen

Peter A. Edelsbrunner
ETH Zürich

Beth Baribault
University of California, Irvine

Useful links

- https://alexanderetz.com/understanding-bayes/
- http://bayesfactor.blogspot.hu/
- How to become a Bayesian: https://psyarxiv.com/ph6sw
- https://marissabarlaz.github.io/portfolio/bayesian/
- http://static.jasp-stats.org/Manuals/Bayesian_Guide_v0.12.2.pdf