Implicit assessment in psychology: Myths, doubts, and practical applications

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Contents

Implicit assessment

In Greenwald & Banaji (1995), implicit attitudes are taken to be:

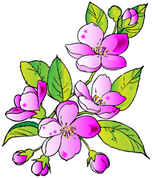
> *Introspectively unidentified–or inaccurately identified–traces of past experience that mediate favorable or unfavorable feelings, thoughts, or actions toward social objects*

IMPLICIT = UNCONSCIOUS

Implicit attitudes express themselves through **automatic associations**

Greenwald, A. G., & Banaji, M. R. (1995) Implicit Social Cognition: Attitudes, Self-Esteem, and Stereotypes. *Psychological Review*, 102-1, doi: 10.1037/0033-295X.102.1.4

Automatic associations



- Beyond one's control
- Activated by triggering stimuli
- Not subject to introspection
- Fast and almost immediate

Automatic associations and the unconscious

Studying automatic associations = studying implicit attitudes

Access the unconscious and investigate it

Automatic associations and the unconscious

Studying automatic associations = studying implicit attitudes

Access the unconscious and investigate it

Fazio & Olson (2003):

> *Being fast is associating snakes with negative attributes does not imply that you are unaware of your negative attitudes towards snakes!*

The only thing you are unaware of: Your attitudes are being assessed → something is indeed implicit

Implicitly assessed constructs vs. unconscious constructs

Fazio, R. H., & Olson, M. A. (2003). Implicit measures in social cognition research: Their meaning and use. *Annual Review of Psychology, 54*(1), 297– 327. https://doi.org/10.1146/annurev.psych.54.101 601.145225

From:

Explicit = conscious Vs. Implicit = unconscious

to:

Explicit = direct Vs. Implicit = indirect

Empirical meaning of implicit

Banaji & Greenwald (2013):

Theoretical definition of implicit as unconscious

Greenwald & Banji (2017), Greenwald & Lai (2020):

Empirical definition of implicit as indirect

Banaji, M. R., & Greenwald, A. G. (2013). *Blindspot: Hidden biases of good people*. Delacorte Press,
Greenwald, A. G., & Banaji, M. R. (2017). The implicit revolution: Reconceiving the relation between conscious and unconscious. *American Psychologist, 72*(9), 861–871. https://doi.org/10.1037/ amp0000238
Greenwald, A. G., & Lai, C. K. (2020). Implicit social cognition. *Annual Review of Psychology, 71*, 419– 445. https://doi.org/10.1146/annurev-psych-010419- 050837

Why...?

- Lack of evidence for supporting the unconsciousness
- Issues with construct validity
- Theory uncommitted definition

IAT

Implicit Association Test

Greenwald et al. (1998):

Table: IAT

Block	Trial	Left key	Right key
1	20	Good	Bad
2	20	Coke	Pepsi
3	20	Coke + Good	Pepsi + Bad
4	40	Coke + Good	Pepsi + Bad
5	20	Pepsi	Coke
6	20	Pepsi + Good	Coke + Good
7	40	Pepsi + Good	Coke + Good

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Coke-Good/Pepsi-Bad Condition

Implicit Association Test

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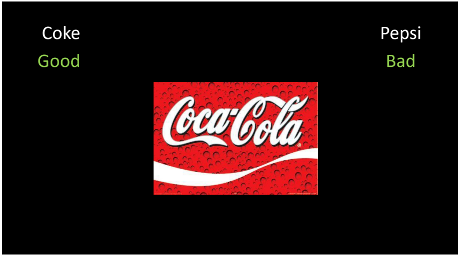
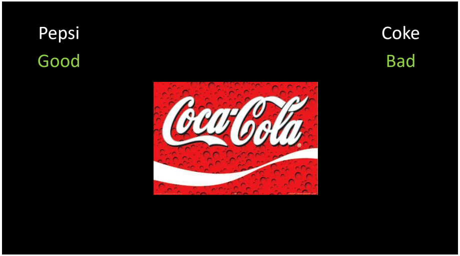
Coke-Good/Pepsi-Bad Condition   Pepsi-Bad/Coke-Good Condition

Coke Good/Pepsi Bad (CGPB)



Pepsi Good/Coke Bad (PGCB)



D score

Greenwald et al. (2003)

$$D_{\mathrm{B6,B3}} = \frac{M_{\mathrm{B6}} - M_{\mathrm{B4}}}{sd_{\mathrm{B6,B3}}} \qquad D_{\mathrm{B7,B4}} = \frac{M_{\mathrm{B7}} - M_{\mathrm{B4}}}{sd_{\mathrm{B7,B4}}}$$

$$D = \frac{D_{\mathrm{B6,B3}} + D_{\mathrm{B7,B4}}}{2}$$

Error responses? Fast responses?

Greenwald, A. G., Nosek, B. A., & Banaji, M. R. (2003). Understanding and using the implicit association test: I. An improved scoring algorithm. *Journal of Personality and Social Psychology, 85*(2), 197– 216. https://doi.org/10.1037/0022-3514.85.2.197

Table: Overview of the D score algorithms.

D *score*	Error inflation	Lower tail treatment
$D1$	Built-in correction	No
$D2$	Built-in correction	Delete trials < 400 *ms*
$D3$	Mean (correct responses) $+ 2sd$	No
$D4$	Mean (correct responses) $+ 600$ *ms*	No
$D5$	Mean (correct responses) $+ 2sd$	Delete trials < 400 *ms*
$D6$	Mean (correct responses) $+ 600$ *ms*	Delete trials < 400 *ms*

What's wrong

A measure in search of a construct

- Lack of correlation with explicit measures
- Lack of correlation with actual behaviors
- Results are hard to reproduce

YES BUT

- Correlation with explicit measures in socially non relevant topics
- The type of behavior one tries to predict

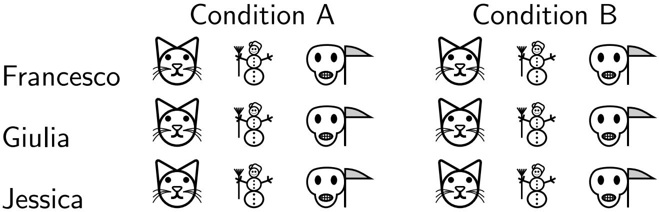
Carlsson, R., & Agerstrom, J. (2016). A closer look at the discrimination outcomes in the IAT literature. *Scandinavian Journal of Psychology, 57*(4), 278–287. doi: https://doi.org/10.1111/sjop.12288

Schimmack, U. (2021). The Implicit Association Test: A method in search of a construct. *Perspectives on Psychological Science, 16*(2), 396–414. https://doi.org/10.1177/1745691619863798

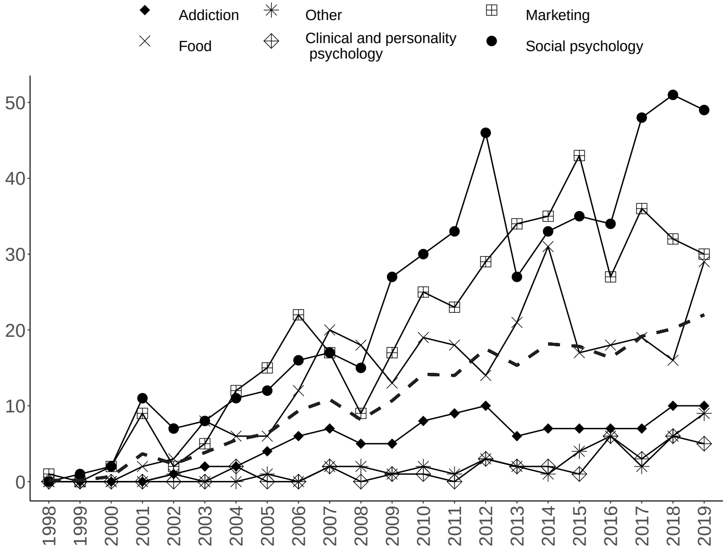
Laziness

- What algorithm did you use? Don't know, don't care
- Error prone procedure
- Lack of automated and free software options

The *D* score



However...


Addiction
Other
Marketing
Food
Clinical and personality psychology
Social psychology
50
40
30
20
10
0
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019

Not the only one

VS

VS

IAT $\rightarrow$ Comparative measure between contrasting objects:

- The contrasted category is not always clear
- The measure of the target category depends on the contrasted category
- Maybe you want an "absolute" measure....

Single Category IAT

Karpinski & Steinman (2006):

Table: SC-IAT

Block	Trial	Left key	Right key
1	24	Good + Coke	Bad
2	72	Good + Coke	Bad
3	24	Good	Bad + Coke
4	72	Good	Bad + Coke

Single Category IAT

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Coke-Good condition

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Coke-Good condition

Coke-Bad condition

Single Category IAT

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4	72	Good	Bad + Coke

Coke-Good condition

Coke-Bad condition

- Response Time Window (rtw, usually 1,500 ms)
- Feedback to each response

Scoring the SC-IAT

$$Dscore = \frac{M_{\mathrm{B2}} - M_{\mathrm{B4}}}{s_{\mathrm{B2,B4}}}$$

- Responses < 350ms $\rightarrow$ discarded
- Responses $> rtw \rightarrow$ discarded
- Error responses $\rightarrow M + 400$ms

Karpinski, A., & Steinman, R. B. (2006). The single category implicit association test as a measure of implicit social cognition. *Journal of Personality and Social Psychology, 91*(1), 16–32. https://doi.org/10 .1037/0022-3514.91.1.16

Go/No-go association Task

Nosek & Banaji (2001):

Table: GNAT

Block	Trials	Signal	Noise
1	16	Good	Bad
2	16	Bad	Good
3	16	Fruit	Bugs
4	16	Bugs	Fruit
5	16	Good + Fruit	Bad + Bugs
	60	Good + Fruit	Bad + Bugs
6	16	Bad + Fruit	Good + Bugs
	60	Bad + Fruit	Good + Bugs
7	16	Good + Bugs	Bad + Fruit
	60	Good + Bugs	Bad + Fruit
8	16	Bad + Bugs	Good + Fruit
	60	Bad + Bugs	Good + Fruit

Go/No-go association Task

Nosek & Banaji (2001):

Table: GNAT

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6	16	Bad + Fruit	Good + Bugs
	60	Bad + Fruit	Good + Bugs
7	16	Good + Bugs	Bad + Fruit
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Go/No-go association Task

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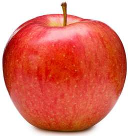
6	16	Bad + Fruit	Good + Bugs
	60	Bad + Fruit	Good + Bugs
7	16	Good + Bugs	Bad + Fruit
	60	Good + Bugs	Bad + Fruit
8	16	Bad + Bugs	Good + Fruit
	60	Bad + Bugs	Good + Fruit

GO

NO GO

Fruit Good



Fruit Good

Nosek, B. A., & Banaji, M. R. (2001). The go/no-go association task. *Social Cognition, 19*(6), 625–666. Q21 https://doi.org/10.1521/soco.19.6.625.20886

Scoring

d' (Green & Swets, 1966):

1. z score of the proportion of hits (correct "go" responses for signal items)
2. z score of the proportion of false alarms (incorrect "go" responses for noise items)
3. Difference between the two scores

Empty cells (no false alarms or misses) $\rightarrow$ 0.35$/\mathrm{numbroftrials}$

Sorting Paired Features Task

Bar-Anan et. al (2009):

Table: SPF

Blocks	Trials	Top-left	Top-right	Bottom-left	Bottom-right
1	48	Dogs+Good	Dogs+Bad	Cats+Good	Cats+Bad
2	48	Dogs+Bad	Dogs+Good	Cats+Bad	Cats+Good
3	48	Cats+Bad	Cats+Good	Dogs+Bad	Dogs+Good
4	48	Cats+Good	Cats+Bad	Dogs+Good	Dogs+Bad

To each pairing → a response key

Bar-Anan, Y., Nosek, B. A., & Vianello, M. (2009). The sorting paired features task: A measure of association strengths. *Experimental Psychology, 56*(5), 329–343. https://doi.org/10.1027/1618-3169. 56.5.329

Correct key: M

Dogs
Bad
Key: Q

Dogs
Good
Key: P

Lovely

Cats
Good
Key: C

Cats
Good
Key: M

Correct key: P

Dogs
Bad
Key: Q

Dogs
Good
Key: P

Lovely

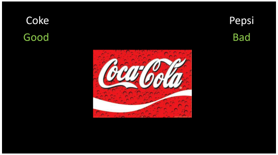
Cats
Good
Key: C

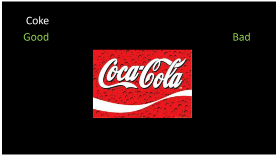
Cats
Good
Key: M

Together

VS

IAT	SC-IAT 1	SC-IAT 2
VS		



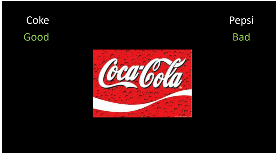


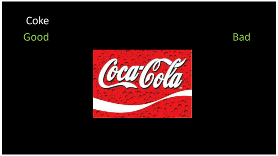
IAT

VS

SC-IAT 1

SC-IAT 2





D score

D Coke

D Pepsi

Stand alone measure:

Multiple measures:

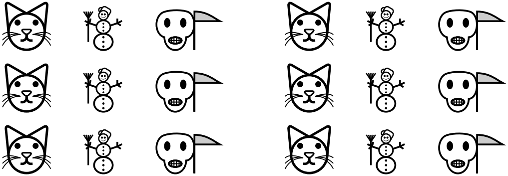
Stand alone measure:

Condition A Condition B

Lara

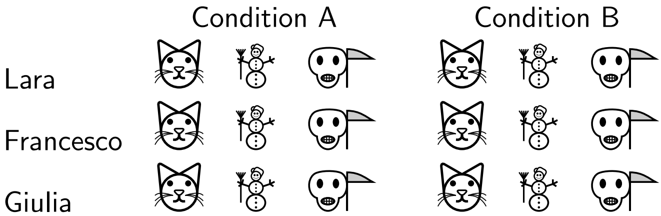
Francesco

Giulia

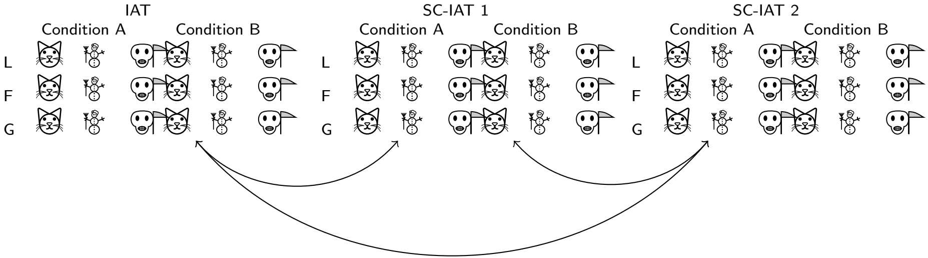


Multiple measures:

Stand alone measure:



Multiple measures:



The workaround

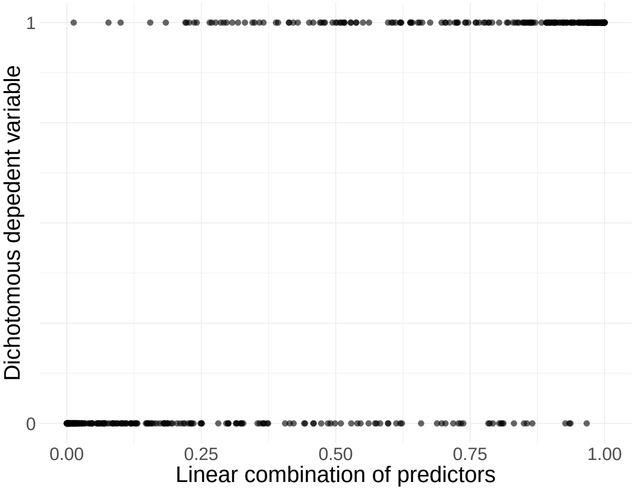
The supermodel(s)

Linear Mixed-Effects Models (LMMs)

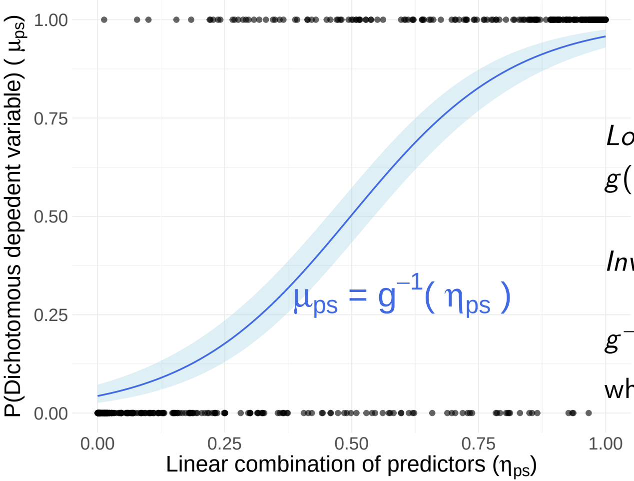
- Account for (potentially) all the sources of variability and dependency
- Gather information at the stimulus level
- Estimate the Rasch and log-normal models

Epifania, O. M., Robusto, E., & Anselmi, P. (2021). Rasch gone mixed: A mixed model approach to the Implicit Association Test. *Testing, Psychometrics, Methodology in Applied Psychology, 28*, 467–483. doi: 10.4473/TPM28.4.5

From Linear to Rasch and log-normal



From Linear to Rasch and log-normal



Logit link function g

$g(\eta_{ps}) = log\left(\frac{\mu_{ps}}{1-\mu_{ps}}\right)$

Inverse g^{-1}

$g^{-1} = \frac{exp(\eta_{ps})}{1+exp(\eta_{ps})}$

where $\eta_{ps} = \theta_p + b_s$

Standard	(G)LM

Rasch model

$$P(x_{ps} = 1) = \frac{exp(\theta_p - b_s)}{1 + exp(\theta_p - b_s)}$$

$$P(x_{ps} = 1) = \frac{exp(\theta_p + b_s)}{1 + exp(\theta_p + b_s)}$$

Log-normal model

$$f(t_{ps}) = \delta_s - \tau_p + \varepsilon$$

$$f(t_{ps}) = \delta_s + \tau_p + \varepsilon$$

Standard

(G)LM

Rasch model

$$P(x_{ps} = 1) = \frac{exp(\theta_p - b_s)}{1 + exp(\theta_p - b_s)}$$

$$P(x_{ps} = 1) = \frac{exp(\theta_p + b_s)}{1 + exp(\theta_p + b_s)}$$

Log-normal model

$$f(t_{ps}) = \delta_s - \tau_p + \varepsilon$$

$$f(t_{ps}) = \delta_s + \tau_p + \varepsilon$$

The expected response y for the observation $i = 1, \dots, I$ for respondent $p = 1, \dots, P$ on stimulus $s = 1, \dots, S$ in condition $c = 1, \dots, C$:

Model 1:

$$y_i = \alpha + \beta_c X_c + \alpha_{p[i]} + \alpha_{s[i]} + \varepsilon_i$$

$$\alpha_p \sim \mathcal{N}(0, \sigma_p^2),$$
$$\alpha_s \sim \mathcal{N}(0, \sigma_s^2).$$

Fixed Effects

Model 2:

$$y_i = \alpha + \beta_c X_c + \alpha_{p[i]} + \beta_{s[i]} c_i + \varepsilon_i$$
$$\alpha_p \sim \mathcal{N}(0, \sigma_p^2),$$
$$\beta_s \sim \mathcal{MVN}(0, \Sigma_{sc}).$$

Random structure

Model 3:

$$y_i = \alpha + \beta_c X_c + \alpha_{s[i]} + \beta_{p[i]} c_i + \varepsilon_i$$
$$\alpha_s \sim \mathcal{N}(0, \sigma_s^2),$$
$$\beta_p \sim \mathcal{MVN}(0, \Sigma_{pc}).$$

Accuracy: $\epsilon \sim Logistic(0, \sigma^2)$
Log-time: $\epsilon \sim \mathcal{N}(0, \sigma^2)$

Accuracy model (Rasch Model estimates):

	Respondent	Stimulus
Model 1	Overall (θ_p)	Overall (b_s)
Model 2	Overall (θ_p)	Condition–specific (b_{sc})
Model 3	Condition–specific (θ_{pc})	Overall (b_s)

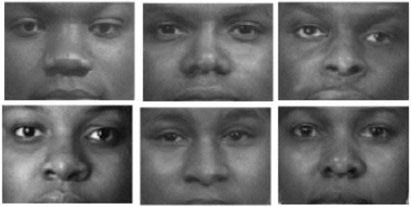
Log-time model (Log-normal Model estimates):

	Respondent	Stimulus
Model 1	Overall (τ_p)	Overall (δ_s)
Model 2	Overall (τ_p)	Condition–specific (δ_{sc})
Model 3	Condition–specific (τ_{pc})	Overall (δ_s)

Rasch gone mixed

Method

12 Target stimuli



16 Attributes (Good, laughter, pleasure, glory, peace, happy, joy, love and and Evil, bad, horrible, terrible, nasty, pain, failure, hate)

Participants: 62 (F $= 48.39\%$, Age $= 24.92 \pm 2.11$ years)

Conditions:

WGBB: White-Good/Black-Bad, 60 trials
BGWB: Black-Good/White-Bad, 60 trials

Model comparison

	Accuracy			Response times		
Model	AIC	BIC	Deviance	AIC	BIC	Deviance
1	3785.87	3813.53	3777.87	4762.63	4797.2	4752.63
2	3784.43	3825.91	3772.43	Aberrant estimates		
3	3786.51	3828.00	3774.51	4399.66	4448.06	4385.66

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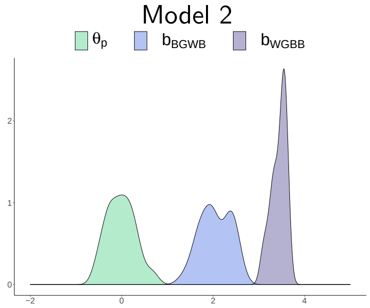
Rasch model:



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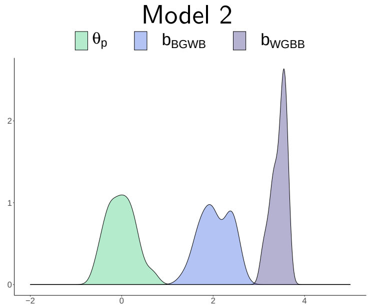
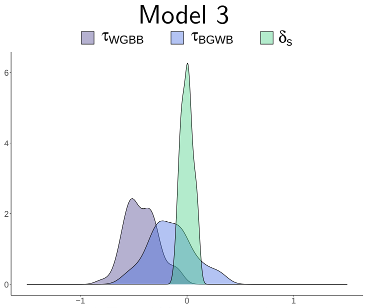
Rasch model:



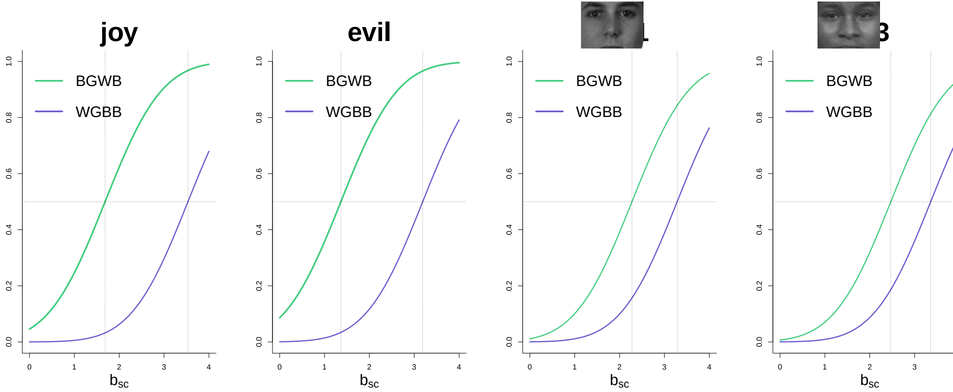
Log-normal model:



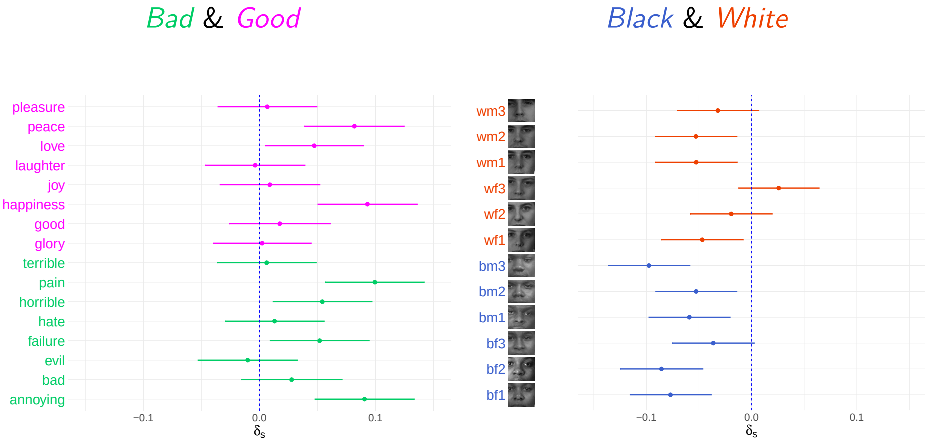
Condition–specific easiness

High contribution stimuli

Low contribution stimuli



Overall time intensity



Make it easy

D-*score*	Error inflation	Delete trials < 400 ms
$D1$	Built-in correction	No
$D2$	Built-in correction	Yes
$D3$	M (correct responses) + 2sd	No
$D4$	M (correct responses) + 600 ms	No
$D5$	M (correct responses) + 2sd	Yes
$D6$	M (correct responses) + 600 ms	Yes

- ☹ Few Open source alternatives
- ☹ Utterly complicated to use
- ☹ No clear information on the algorithm they compute
- ☹ No graphical representation of the results

D-score	Error inflation	Delete trials < 400 ms
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- ☹ No graphical representation of the results

Something Open Source, able to compute multiple scores, and to provide nice graphical representations

Make it easy & Clear

implicitMeasures package DOI:10.21105/joss.02394 :

Function	Description
clean_iat()	Prepare and clean IAT data
clean_sciat()	Prepare and clean SC-IAT data
compute_iat()	Compute IAT *D-score*
compute_sciat()	Compute SC-IAT *D-score*
descript_d()	Descriptive table of *D-score*s (even in LaTeX)
d_density()	Plot IAT or SC-IAT scores (distribution)
d_point()	Plot either IAT or SC-IAT scores (points)
IAT_rel()	IAT reliability
multi_dsciat()	Plot SC-IATs scores
multi_dscore()	Compute and plot multiple *D-score*s
raw_data()	Dataset with one IAT and two SC-IATs

- implicitMeasures: Introduction to IAT, SC-IAT, and *D score*s.
- IAT-example: Package illustration on IAT data
- SC-IAT-example: Package illustration on SC-IAT data

Make it even easier

Source code on GitHub

DOI: 10.3389/fpsyg.2019.02938