

Filling the gap between implicit and behavior: A Rasch modeling of the Implicit Association Test

Ottavia M. Epifania, Anselmi Pasquale, Egidio Robusto

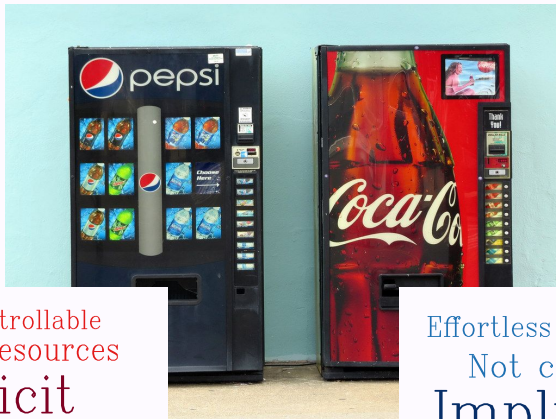
University of Padova, Italy

Cognitive Science Arena,
Bressanone-Brixen,
February 7th-9th 2020





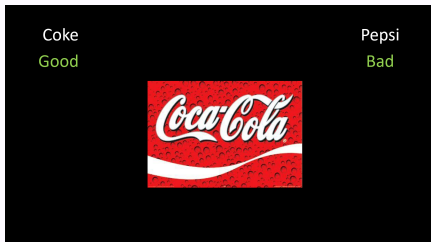
Controllable
Cognitive resources
Explicit
Deliberate



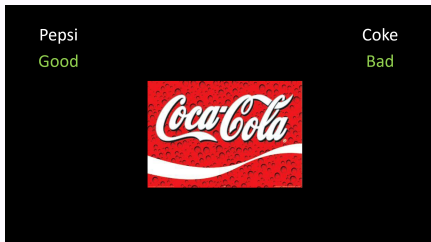
Controllable
Cognitive resources
Explicit
Deliberate

Effortless
Not controllable
Implicit
Automatic

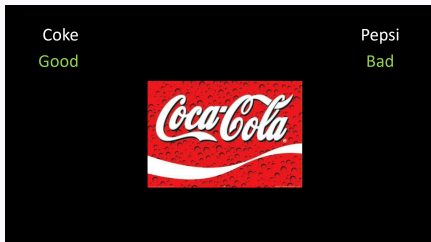
Coke Good/Pepsi Bad (CGPB)



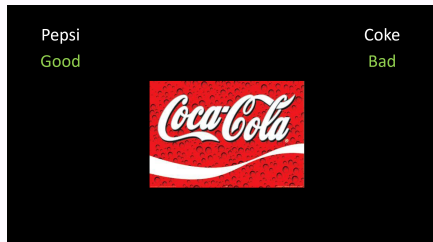
Pepsi Good/Coke Bad (CGPB)



Coke Good/Pepsi Bad (CGPB)



Pepsi Good/Coke Bad (PGCB)



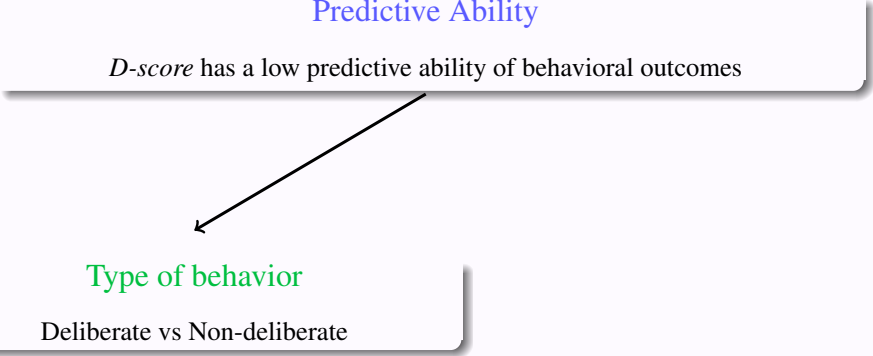
$$D_{score} = \frac{M_{cgpb} - M_{pgcb}}{s_{cgpb,pgcb}}$$

Predictive Ability

D-score has a low predictive ability of behavioral outcomes

Predictive Ability

D-score has a low predictive ability of behavioral outcomes



Type of behavior

Deliberate vs Non-deliberate

Predictive Ability

D-score has a low predictive ability of behavioral outcomes

```
graph TD; A["D-score has a low predictive ability of behavioral outcomes"] --> B["Type of behavior"]; A --> C["Computation"]; B --> D["Deliberate vs Non-deliberate"]; C --> E["IAT data structure completely ignored"];
```

Type of behavior

Deliberate vs Non-deliberate

Computation

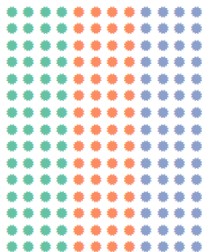
IAT data structure completely ignored

Respondents

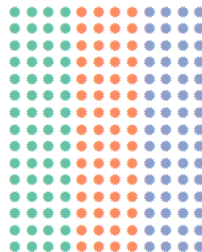
D-score



Condition 1






Condition 2





Linear Mixed Effect Models (LMMs) allow for:

-  Accounting for (potentially) all the sources of variability and dependency
-  Gathering information at the stimuli level
-  Estimating Rasch and Log-normal models parameters

Investigate the predictive ability of the IAT

Investigate the predictive ability of the IAT

```
graph TD; A[Investigate the predictive ability of the IAT] --> B[D-score]; A --> C[Rasch and Log-normal model estimates];
```

D-score

Rasch and Log-normal model estimates

Investigate the predictive ability of the IAT

D-score

Rasch and Log-normal model estimates

Rasch model:
GLMM on accuracy responses

Ability

θ

Easiness

b

Investigate the predictive ability of the IAT

D-score

Rasch and Log-normal model estimates

Rasch model:

GLMM on accuracy responses

Ability

θ

Easiness

b

Log-normal model:

LMM on log-time responses

Speed

τ

Time intensity

δ

Investigate the predictive ability of the IAT

D-score

Rasch and Log-normal model estimates

Rasch model:

GLMM on accuracy responses

Log-normal model:

LMM on log-time responses

Ability

θ

Easiness

b

Speed

τ

Time intensity

δ

Respondents

Investigate the predictive ability of the IAT

D-score

Rasch and Log-normal model estimates

Rasch model:
GLMM on accuracy responses

Log-normal model:
LMM on log-time responses

Ability

θ

Easiness

b

Speed

τ

Time intensity

δ

Respondents

Stimuli

The expected response y for the observation $i = 1, \dots, I$ for respondent $j = 1, \dots, J$ on stimulus $k = 1, \dots, K$ in condition $l = 1, \dots, L$:

Model 1:

$$y_i = \text{logit}^{-1}(\alpha + \beta l_i + \alpha_{k[i]} + \beta_{j[i]} l_i + \epsilon_i)$$

$\alpha_k \sim \mathcal{N}(0, \sigma_k^2)$, between-stimuli variability.

$\beta_l \sim \mathcal{MVN}(0, \Sigma_l)$, within-respondents between-conditions variability

Model 2:

$$y_i = \text{logit}^{-1}(\alpha + \beta l_i + \alpha_{j[i]} + \beta_{k[i]} l_i + \epsilon_i)$$

$\alpha_j \sim \mathcal{N}(0, \sigma_j^2)$, between-respondents variability.

$\beta_k \sim \mathcal{MVN}(0, \Sigma_l)$, within-stimuli between-conditions variability.

Model 3:

$$y_i = \text{logit}^{-1}(\alpha + \beta l_i + \alpha_{j[i]} + \alpha_{k[i]} + \epsilon_i)$$

$\alpha_j \sim \mathcal{N}(0, \sigma_j^2)$, between-respondents variability.

$\alpha_k \sim \mathcal{N}(0, \sigma_k^2)$, between-stimuli variability.

Accuracy: $\epsilon \sim \mathcal{L}(0, \sigma^2)$

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

Fixed Effects

Accuracy model (Rasch Model estimates):

	Respondents parameters	Stimuli parameters
Model 1	Condition-specific (θ_{jl})	Overall (b_k)
Model 2	Overall (θ_j)	Condition-specific (b_{kl})
Model 3	Overall (θ_l)	Overall (b_k)

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

	Respondents parameters	Stimuli parameters
Model 1	Condition-specific (τ_{jl})	Overall (δ_k)
Model 2	Overall (τ_j)	Condition-specific (δ_{kl})
Model 3	Overall (τ_j)	Overall (δ_k)

Method

Valenced words

- Positive words (n = 13): good, laughter, pleasure, glory, peace, happiness, joy, love, marvelous, beautiful, excellent, paradise, wonderful
- Negative words (n = 13): evil, bad, horrible, terrible, annoying, pain, failure, hate, nasty, disaster, agony, ugly, disgust

Chocolate images (Milk = 7, Dark = 7)



Behavioral choice at the end of the experiment

Participants: 74 (F = 71.62%, Age = 24.08 ± 2.88 years), $I_{jl} = 60$

Results

Model	Accuracy			Response times		
	AIC	BIC	Deviance	AIC	BIC	Deviance
1	Failed to converge			7159.23	7208.87	7145.23
2	3625.58	3668.13	3613.58	Aberrant estimates		
3	3627.71	3656.07	3619.71	7856.45	7891.91	8875.00

Model	Accuracy			Response times		
	AIC	BIC	Deviance	AIC	BIC	Deviance
1	Failed to converge			7159.23	7208.87	7145.23
2	3625.58	3668.13	3613.58	Aberrant estimates		
3	3627.71	3656.07	3619.71	7856.45	7891.91	8875.00

Accuracy model:

Model 2

- b_{dgmb} : Stimuli easiness in Dark-Good/Milk-Bad Condition.
- b_{mgdb} : Stimuli easiness in Milk-Good/Dark-Bad Condition.
- Overall participants' ability (θ_j), across stimuli/conditions.

Model	Accuracy			Response times		
	AIC	BIC	Deviance	AIC	BIC	Deviance
1	Failed to converge			7159.23	7208.87	7145.23
2	3625.58	3668.13	3613.58	Aberrant estimates		
3	3627.71	3656.07	3619.71	7856.45	7891.91	8875.00

Accuracy model:

Model 2

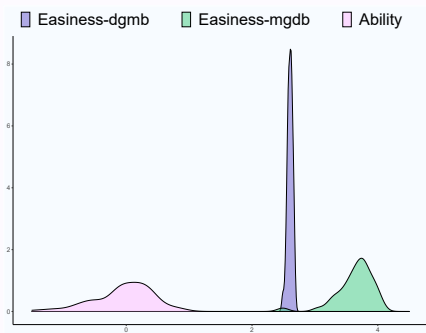
- b_{dgmb} : Stimuli easiness in Dark-Good/Milk-Bad Condition.
- b_{mgdb} : Stimuli easiness in Milk-Good/Dark-Bad Condition.
- Overall participants' ability (θ_j), across stimuli/conditions.

Log-time model:

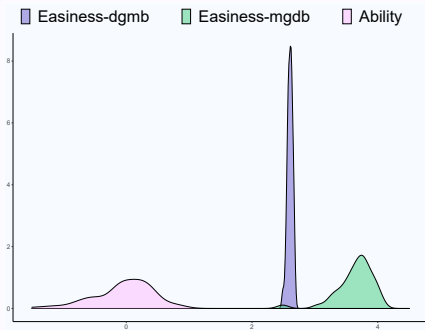
Model 1

- τ_{dgmb} : Participants' speed in Dark-Good/Milk-Bad Condition.
- τ_{mgdb} : Participants' speed in Milk-Good/Dark-Bad Condition.
- Overall stimuli time intensity (δ_k), across participants/across conditions.

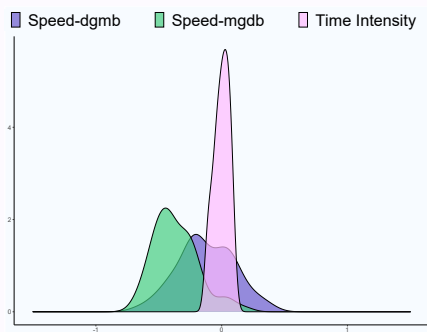
Rasch model:



Rasch model:



Log-normal model:



Dark Chocolate Choice
(DCC) = 0

Milk Chocolate Choice
(MCC) = 1

Differential measures:

Choice \sim *D-score*

Choice \sim *Speed-differential*

Single components:

Choice $\sim M_{dgmb} + M_{mgdb}$

Choice $\sim \tau_{dgmb} + \tau_{mgdb}$

$$\textit{speed-differential} = \tau_{dgmb} - \tau_{mgdb}$$

		Expected			
		Dark	Milk		
Observed	Dark	<i>a</i>	<i>b</i>	<i>a + b</i>	DCCs
	Milk	<i>c</i>	<i>d</i>	<i>c + d</i>	MCCs
		<i>a + c</i>	<i>b + d</i>		

$$\frac{a+d}{a+b+c+d}$$

General Accuracy (i.e., ratio between model correctly identified choices and total number of choices)

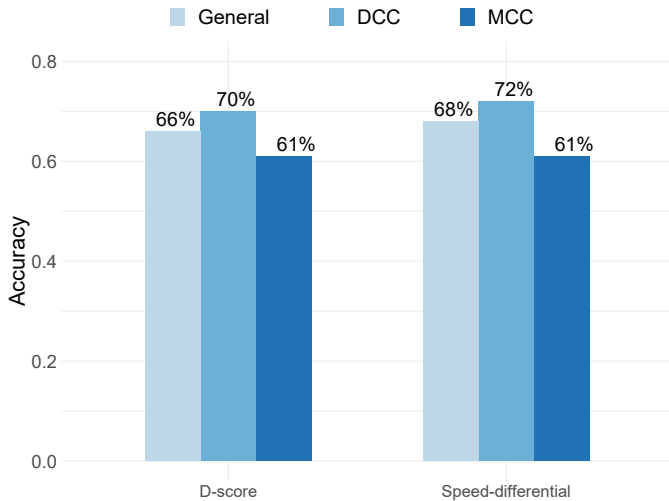
$$\frac{a}{a+b}$$

DCC Accuracy (i.e., ratio between model correctly identified DCCs and observed number of DCCs)

$$\frac{d}{c+d}$$

MCC Accuracy (i.e., ratio between model correctly identified MCCs and observed number of MCCs)

Differential measures

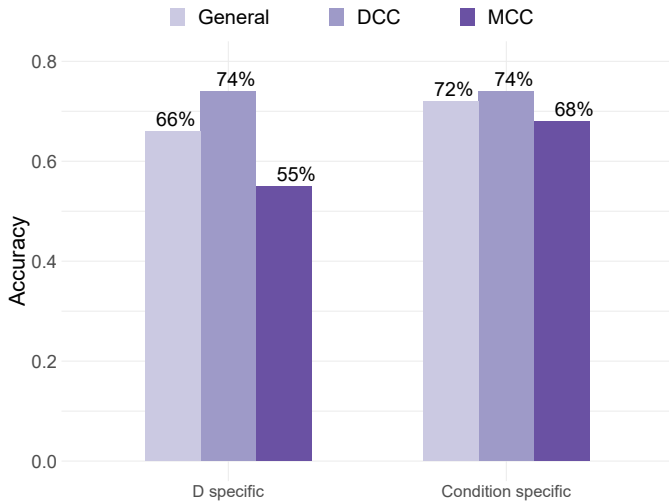


Nagelkerke R^2

0.19

0.20

Single components



Nagelkerke R²

0.21

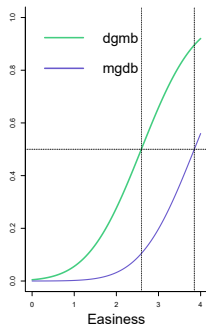
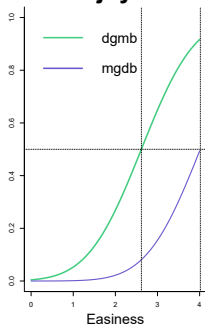
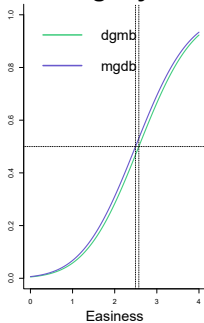
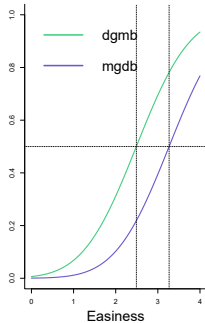
0.20

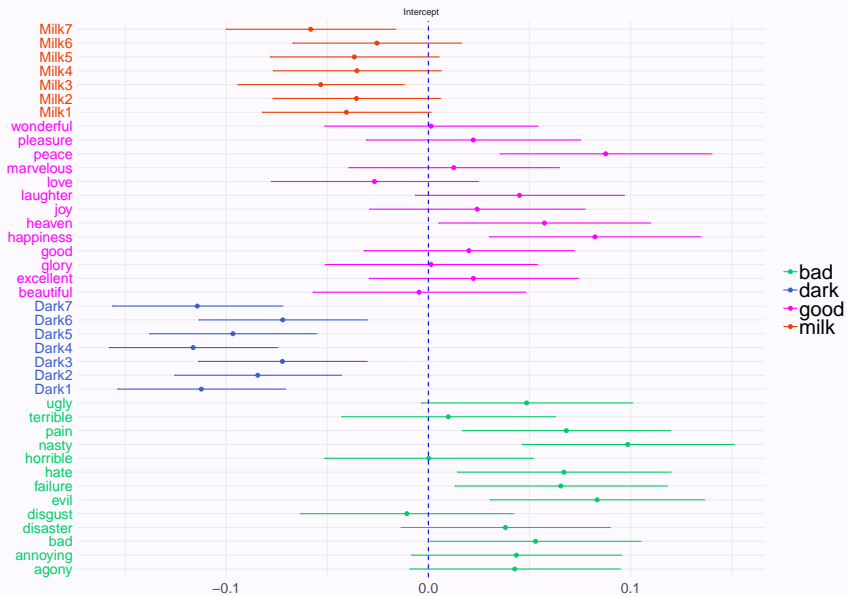
Not over yet!

Item Characteristic Curves (ICC)

High contribution stimuli

Low contribution stimuli

hate**joy****agony****Dark1**



Conclusions

IAT functioning & meaning

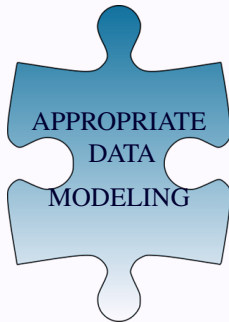
Fine-grained analysis:

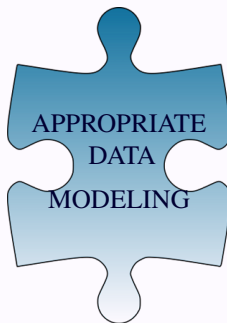
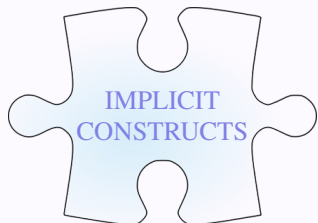
- ① Stimuli level:
 - Malfunctioning stimuli
 - Stimuli driving the IAT effect

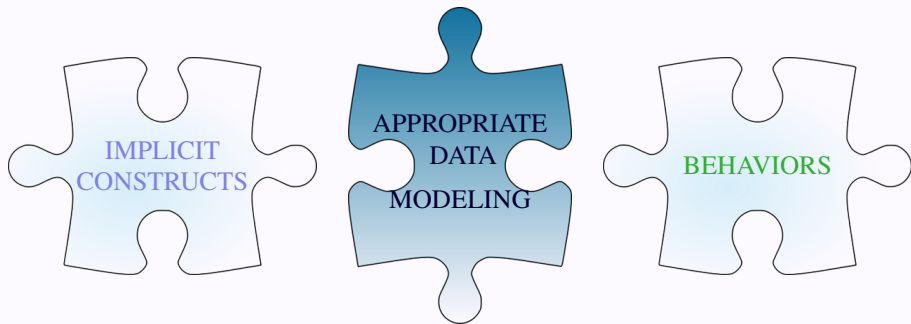
- ② Respondents' level:
 - Respondents' accuracy consistent between conditions
 - Respondents' speed affected by the associative condition

Choice prediction

- Differential measures vs single components
- Random noise with appropriate random structure & behavioral outcomes







Thank you!



L^AT_EX

