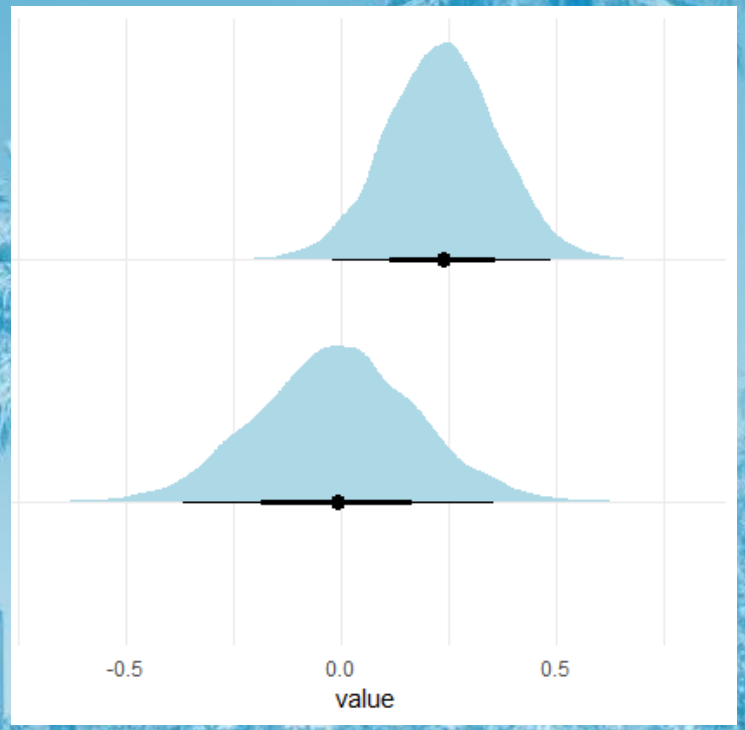
Kingston University London



Emotions and Facial Expressions:
Theoretical, Operational, Methodological, and Statistical Considerations for Modern Open Research

Mircea Zloteanu
Kingston University London

ME

- Senior Lecturer in Investigative Psychology & Criminology at Kingston University London (Present)
- Experimental Psychologist (PhD)
- Focus on judgement under uncertainty
- Open Science & Reproducibility
- Some Bayesian stuff, some R

Figuring Stuff Out (stats blog)
https://mzstats.blogspot.com/

Deception Detection

Judgement and Bias

Emotions

Facial Expressions

Interrogations

Sharing Economy & User decision-making

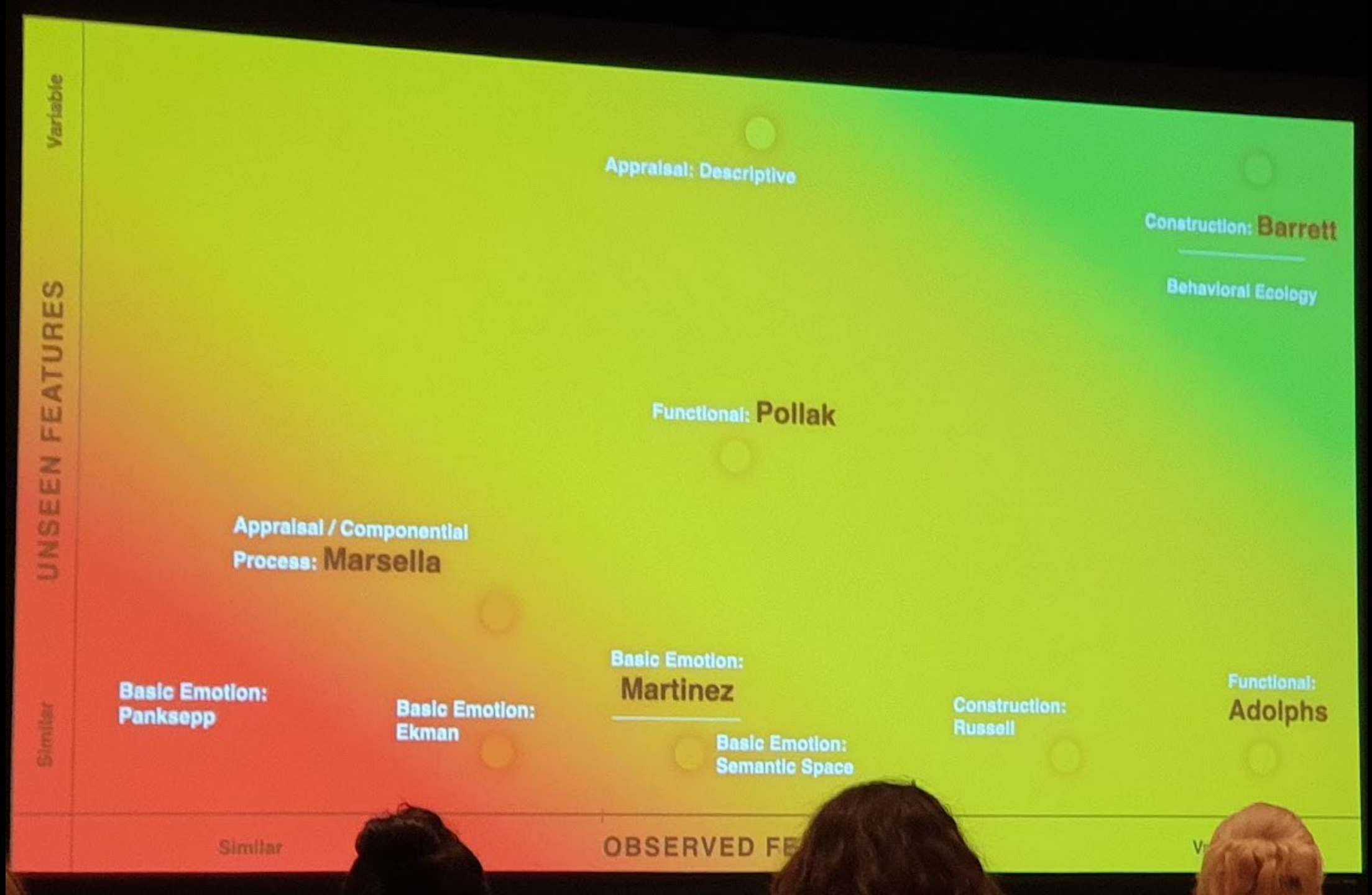
Embodied Effects

Group Decision-Making

Kingston University London

EMOTION THEORY

[Theoretical Aspects]


Variable
UNSEEN FEATURES
Similar
Appraisal: Descriptive
Construction: Barrett
Behavioral Ecology
Functional: Pollak
Appraisal / Componential
Process: Marsella
Basic Emotion:
Panksepp
Basic Emotion:
Ekman
Basic Emotion:
Martinez
Basic Emotion:
Semantic Space
Construction:
Russell
Functional:
Adolphs
Similar
OBSERVED FE
V

EMOTIONS: UNIVERSAL OR SOCIAL

no consensus on what is an "emotion"

Basic Emotion Theory (BET)

- Universal (same everywhere)
- Require no learning (innate)
- Cross-culturally understood
- Different real and fake expressions
- Vestigial behaviours which need to be "decoded"

facial expressions don't represent all underlying emotions

Behavioural Ecology View (BECV)

- Communication signals (easily understood)
- Co-evolved to be understood by peers
- Vary from group to group (culture, society, etc.)
- Doesn't assume "genuine" and "fake" expressions differ

BEHAVIOURAL DIFFERENCES? "RELIABLE" MUSCLES?

Comparison of Blind and Sighted athletes who just lost a match for a medal

Non-Duchenne Smile

Duchenne Smile

HOWEVER
No such reliable muscles (e.g., Krumhuber & Manstead, 2009)
Authenticity discrimination is poor (e.g., Hess & Kleck, 1994)

EMOTIONAL AUTHENTICITY JUDGEMENTS

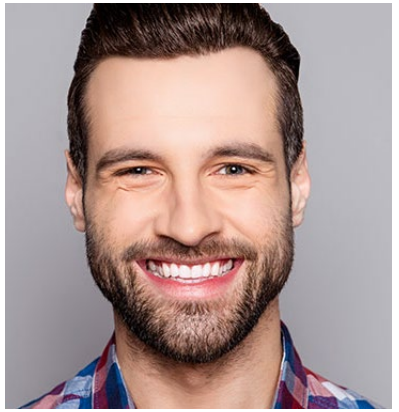
People are good at **classifying** emotional facial expressions (Ekman, 2003)*

Less capable at **discriminating** genuine from non-genuine expressions (Zloteanu, et al., 2018, 2020)

Little evidence for "reliable muscles" (e.g., Krumhuber & Manstead, 2009)

Few studies are designed to make directional claims; having only 2 categories in the stimuli is not informative – nor does it reflect reality

How we operationalize expressions matter! (as we will see shortly)



Label this expression

"Happiness"
CORRECT!

Is the person happy?

"Umm, yes?"
INCORRECT

These are NOT the same task!

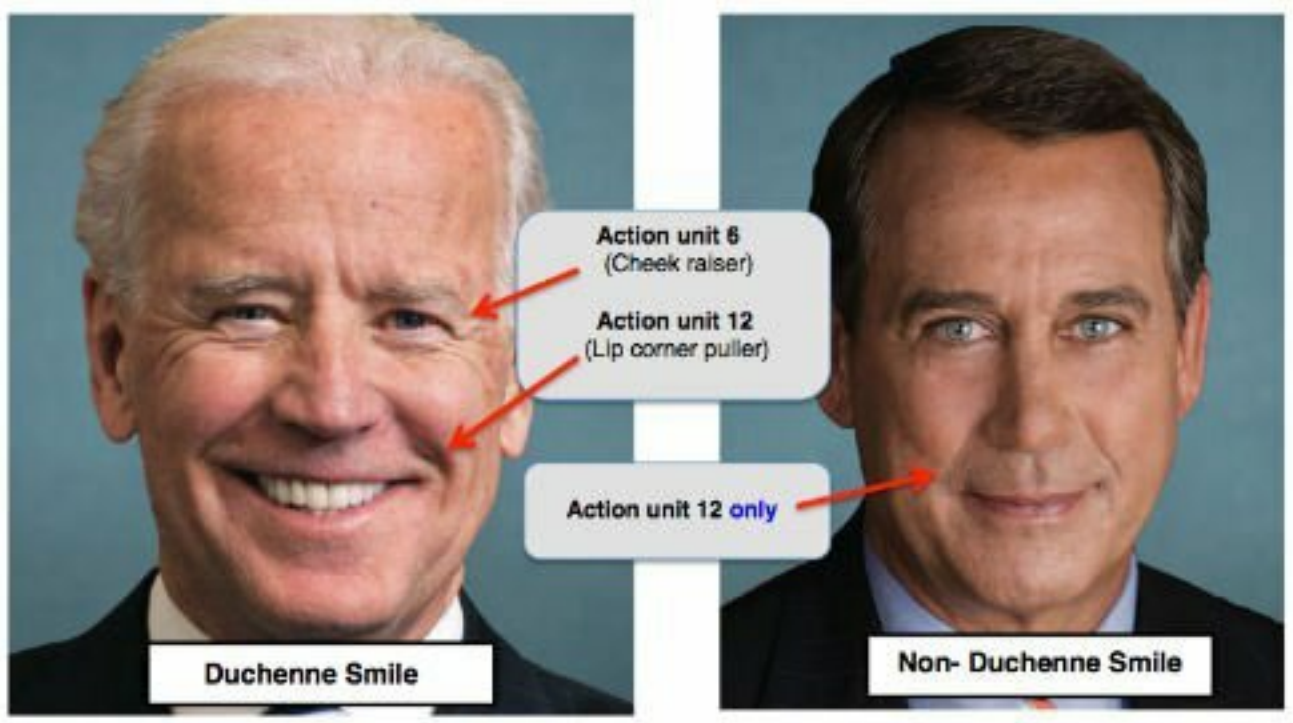
FRAMEWORK YOU USE AFFECTS EVERYTHING!

- **Assumptions**
  Discrete vs variable | Involuntary vs Communicative | Authenticity exists vs Authenticity is a perceptual feature
- **Predictions**
  About effects (size, variance) and judgement processes (detection, training, bias, perception)
- **Methodology**
  often non-overlapping e.g., discrete, prototypical, cue-based sets vs production/context-based sets
- **Measurement**
  different effects e.g., detection accuracy (%) vs judgement shift
- **Conclusions**
  e.g., emotion recognition is linked to “reading” subtle “cues” vs emotions are communicative signals

FOR INSTANCE: STIMULI

If you ascribe to BET:

- Instruct "senders" (dif. ways)
- Activation of specific facial muscles
- Use coding (FACS) to check
- If activation = pattern [correct]
- If activation != pattern [incorrect]



CORRECT ACTIVATION
Use in "Genuine"

INCORRECT ACTIVATION
Use in "Non-Genuine"

[Intellective task]

FOR INSTANCE: STIMULI

If you ascribe to BECV

- Construct situation to elicit an emotion
- Record the activity
- You “ignore” variance
- No coding per se
- Group based on context, not performance

CONTEXT

[Judgemental Task]

BRIEF ASIDE: DECEPTION DETECTION

[My interests]

DETECTING LIES AND TRUTHS

People lie often and for various reasons

However, detection rates are ~54%

Bias towards believing others are honest

No <u>one</u> definitive cue of lying

Meta-analyses find (inconsistent) clusters of “cues”

EMOTION RECOGNITION AND DECEPTION DETECTION

Traditional Logic (BET):

1. emotional "cues" differ based on genuine and deceptive behaviour
2. emotion recognition relates to accurately "reading" emotional cues (e.g., empathy)
3. empathy may play a role in authenticity judgements

Prediction: Empathic people are better at spotting deceivers' *leaked* emotions

New Logic (BECV):

1. empathy relates to emotion recognition
2. **but,** only when those emotions <u>are genuine</u>
3. when the cues are insincere, empathy will **hinder** deception detection (misinterpretation)

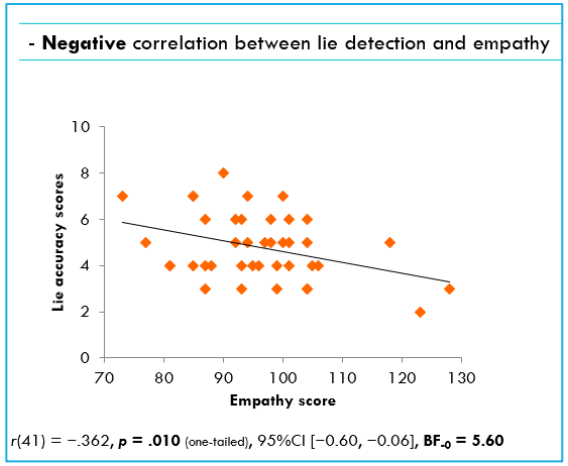
Prediction: Higher levels of empathy will negatively relate with emotional lie detection

DECEPTION DETECTION RESULTS: INTERPRETATION

Empathic judges perform ***worse*** at lie detection.

Explanations:

- Empathic people have difficulty discriminating fabricated emotional cues (**BECV compatible**) (BET incompatible)
- Empathy relates to **speed of processing** of emotional information (lower threshold)
  - Emotional information is misinterpreted as signal for truth



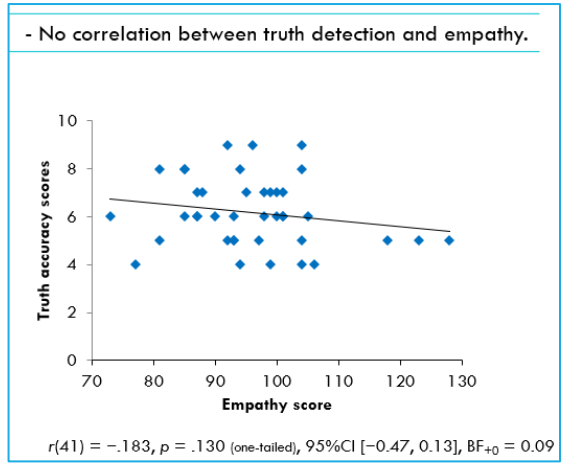


Table 1. Parameter estimates, EE, 95% HDI, Bayes factor, and MPE (N = 106).

Model	Coefficient	95% HDI					
		Estimate	EE	Lower	Upper	BF_{10}	MPE (%)
Null model	**Intercept**	**−0.09**	**0.04**	**−0.17**	**−0.02**	**0.07**	**99.38**
	BT	−0.08	0.07	−0.21	0.05	0.01	88.56
	NT	−0.04	0.06	−0.17	0.08	$7.29e^{-3}$	75.27
	AU	**−0.79**	**0.07**	**−0.92**	**−0.66**	$\mathbf{4.79e^{11}}$	**100.00**
	AE	**0.37**	**0.05**	**0.27**	**0.47**	$\mathbf{5.69e^{4}}$	**100.00**
	Veracity (truth)	**0.49**	**0.05**	**0.39**	**0.58**	$\mathbf{6.90e^{8}}$	**100.00**
	BT:AU	−0.14	0.12	−0.37	0.09	0.02	87.81
	NT:AU	−0.10	0.11	−0.32	0.12	0.02	81.17
	BT:AE	−0.06	0.09	−0.24	0.13	0.01	73.29
	NT:AE	−0.09	0.09	−0.26	0.09	0.01	83.85
	BT:Veracity	0.06	0.09	−0.11	0.23	$9.86e^{-3}$	76.27
	NT:Veracity	0.13	0.08	−0.03	0.30	0.03	94.28
	AU:Veracity	0.14	0.09	−0.04	0.32	0.03	93.02
	AE:Veracity	0.03	0.08	−0.12	0.17	$7.15e^{-3}$	63.19
	BT:AU:Veracity	−0.04	0.17	−0.37	0.29	0.02	59.20
	NT:AU:Veracity	0.16	0.16	−0.15	0.48	0.02	83.78
	BT:AE:Veracity	0.03	0.13	−0.24	0.29	0.01	58.00
	NT:AE:Veracity	−0.24	0.13	−0.48	0.01	0.07	96.89

Original Article

QJEP

Quarterly Journal of Experimental Psychology
2021, Vol. 74(5) 910–927

DOI: 10.1177/1747021820978851
qjep.sagepub.com
SAGE

Veracity judgement, not accuracy: Reconsidering the role of facial expressions, empathy, and emotion recognition training on deception detection

Mircea Zloteanu[1,2], Peter Bull[3,4], Eva G Krumhuber[5] and Daniel C Richardson[5]

Abstract

People hold strong beliefs about the role of emotional cues in detecting deception. While research on the diagnostic value of such cues has been mixed, their influence on human veracity judgements is yet to be fully explored. Here, we address the relationship between emotional information and veracity judgements. In Study 1, the role of emotion recognition in the process of detecting naturalistic lies was investigated. Decoders' veracity judgements were compared based on differences in trait empathy and their ability to recognise microexpressions and subtle expressions. Accuracy was found to be unrelated to facial cue recognition and negatively related to empathy. In Study 2, we manipulated decoders' emotion recognition ability and the type of lies they saw: experiential or affective (emotional and unemotional). Decoders received either emotion recognition training, bogus training, or no training. In all scenarios, training did not affect veracity judgements. Experiential lies were easier to detect than affective lies; however, affective unemotional lies were overall the hardest to judge. The findings illustrate the complex relationship between emotion recognition and veracity judgements, with abilities for facial cue detection being high yet unrelated to deception accuracy.

Keywords

Emotion recognition; deception detection; lie; training; facial expression; empathy

Received: 29 September 2019; revised: 12 November 2020; accepted: 15 November 2020

Introduction

Decades of deception research have consistently found that human lie detection ability is poor (Bond & DePaulo, 2006). People are also overconfident in their ability (Holm & Kawagoe, 2010) and biased towards assuming that most statements are honest (i.e., truth-biased; Levine et al., 1999). Some scholars argue that decoders' lacklustre performance is due to their inability to detect subtle behavioural differences between liars and truth-tellers, especially related to emotions (Ekman, 2003a). Implicitly, this assumes that (1) there exist diagnostic behavioural cues of deceit, and (2) decoders can make rational veracity judgements if they use such cues. This approach has resulted in a theoretical standstill (partly due to the low reliability of behavioural cues in predicting deception) and a lack of research on people's veracity judgement processes.

Indeed, there are few theoretical models of human veracity judgement, with both classical (e.g., Zuckerman, DePaulo, & Rosenthal, 1981) and newer attempts (e.g., Levine, 2014b; Street, 2015) placing a growing emphasis on decoders' perception of alleged "cues of deceit," thereby using accuracy as the primary metric of interest. Here, we recontextualise human deception detection, moving away from a focus on accuracy (i.e., the correct perception and interpretation of behavioural cues) towards a

[1]Department of Psychology, Teesside University, Middlesbrough, UK
[2]Department of Criminology and Sociology, Kingston University, London, UK
[3]Department of Psychology, University of York, York, UK
[4]Department of Psychology, University of Salford, Salford, UK
[5]Department of Experimental Psychology, University College London, London, UK

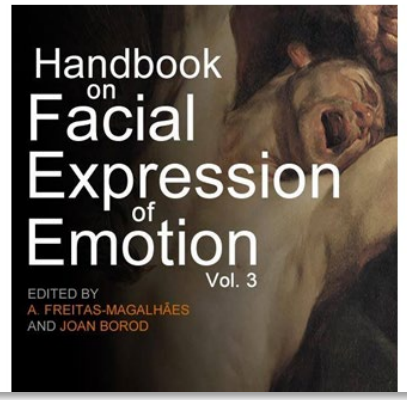
Corresponding author:
Mircea Zloteanu, Department of Criminology and Sociology, Kingston University, London KT1 2EE, UK.
Email: m.zloteanu@kingston.ac.uk

Reconsidering Facial Expressions and Deception Detection

Mircea Zloteanu

The function of facial expressions of emotions in detecting deception has been a hotly debated topic. One side argues that liars and truth-teller display different facial expressions which can be used as diagnostic cues of deceit. The other argues that such cues are rare, unpredictable, and ambiguous, and as such are unreliable to detecting deception. This chapter overviews facial expression in deception detection, separating their alleged diagnostic value as cues to deception from that of strategic affective signals in human communication. Building upon our current understanding and research in the deception and emotion fields, I elaborate on relevant but underdeveloped concepts, and address how the process of detecting lies can be influenced by facial expressions of emotions. I critically evaluate several assumptions of the emotion-based approach to detecting deception, illustrating the limitations of this view. A strong emphasis is placed on expanding the role of facial expressions in deception, by considering both the encoder-decoder and the affective-signaling perspectives. I propose a careful distinction between genuine cues and deceptive cues, considering the importance of emotional authenticity and sender intent. Finally, I consider the role of facial expressions of emotion in human veracity judgment and future directions for the field of emotion and deception in light of the current propositions. This is done in light of recent propositions to the use of automated lie detection tools on the basis of facial expressions of emotion. I argue that caution must be given to such techniques, elaborating on the flawed underpinnings guiding their decisions, and make considerations for the future of this research.

*****



The role of emotions in detecting deception

Mircea Zloteanu

Abstract

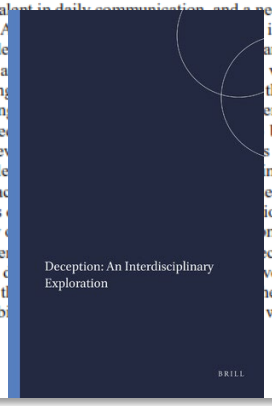
The ability to recognise the emotional states of others is believed to facilitate the detection of deception, but the exact way in which individuals use emotion information has not been fully addressed. Currently, the importance of the stakes to the liar in emotion cue production and the way that this information is utilised by different observer is put into focus. Individual differences in empathic ability are proposed to be a crucial moderator of the relationship between emotion recognition and deception detection. This ability may facilitate deception detection in certain circumstances but may hinder accuracy in others. The aim of this paper is to provide an overview of the way emotions relate to both the process of deception and its detection, and propose avenues of research into this area. A formulation of a model regarding how emotions are expressed and used in various types of lies is proposed, providing testable predictions about the outcome of the deception detection process.

Key Words: Deception Detection, Empathy, Emotion Recognition, Micro-expressions, Subtle expressions, Accuracy.

*****

1. Deception Detection

Deception is defined as the act of deliberately instilling a false belief in another individual. [1,2] It is prevalent in daily communication, and a necessary component of social interactions. [3,4,5] A
is common, they seem
unable to accurately de
arch on deception has
found that individuals a
when others are lying
to them, usually findin
than chance [6] and are
biased towards believin
en than not, regardless
of actual veracity. [7] De
be influenced by age,
gender, experience or ev
s poor detection rate is
the absence of a single
ng it very difficult to
uncover deception in fac
earch on deception has
found that reliable cues
ion and type of lie. [9,10]
A prominent theory
n of such cues focuses
on the emotions experie
ceiving. Leakage
theory states that when
verbal information,
produced as a result of t
he liar, which can
betray the lie. The inhib
will experience strong

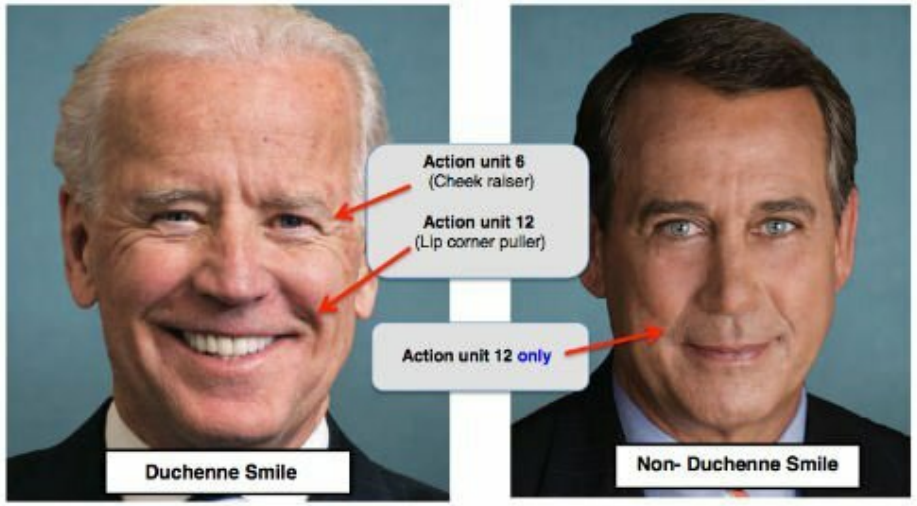


BACK TO EMOTION RESEARCH

AUTHENTICITY DISCRIMINATION

[Operationalisation]

FRAMEWORK DETERMINES STUDY DESIGN

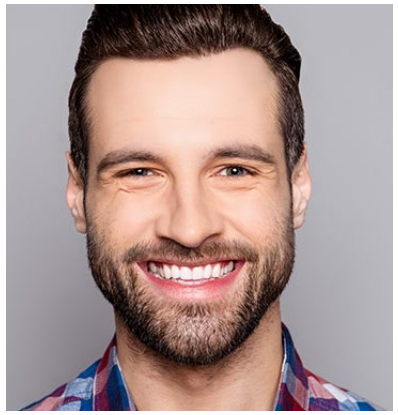


CORRECT ACTIVATION
Use in "Genuine"

INCORRECT ACTIVATION
Use in "Non-Genuine"

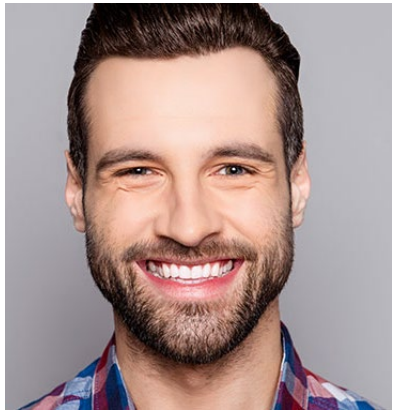
CONTEXT

FRAMEWORK DETERMINES STUDY DESIGN



Label this expression

"Happiness"
CORRECT!

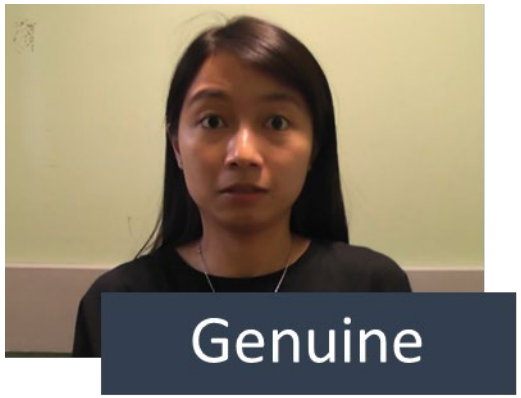


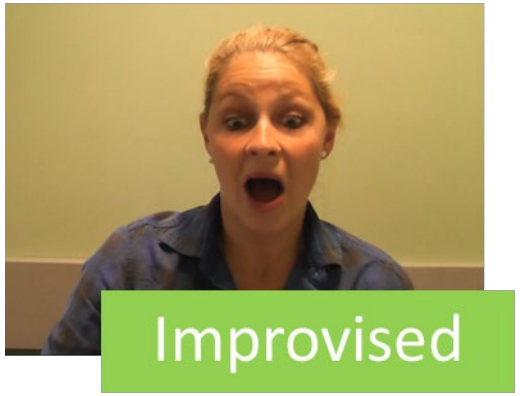
Is the person happy?

"Umm, yes?"
INCORRECT

Happy	2	3	4	5	6	7	8	9	Not Happy

EXAMPLE FROM MY RESEARCH





Can people produce genuine-looking facial displays?

Are all deliberate (deceptive) facial displays the same?

Does the production (elicitation) method matter?

We investigated **surprise.**

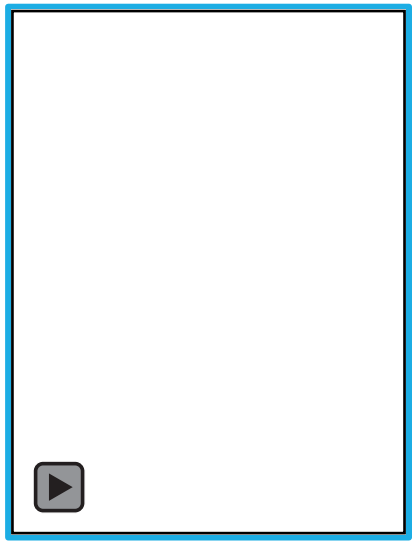
Research Questions:

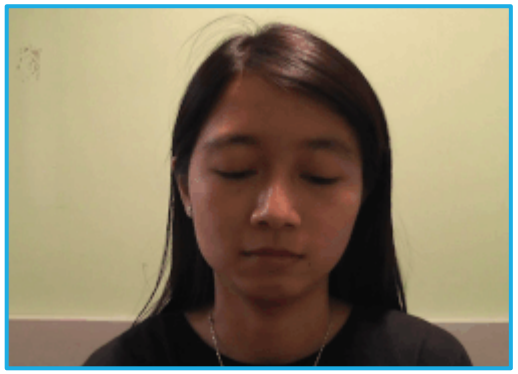
- Presentation format matters (dynamic v static)
- Production method matters (explains inconsistent results)
- People can produce convincing facial displays

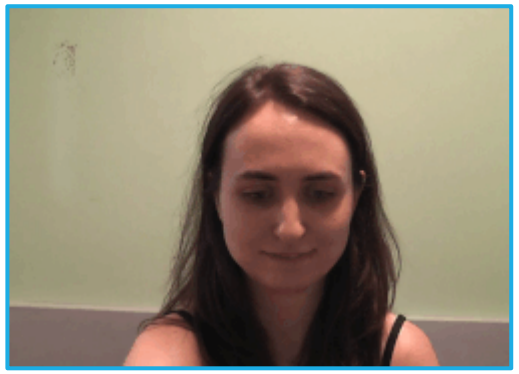
DELIBERATE EXPRESSIONS

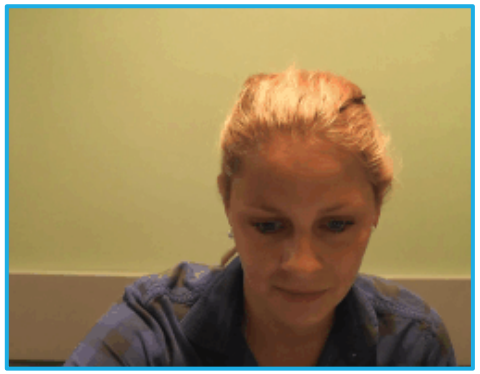
Can senders produce genuine-looking expressions which can ‘fool’ decoders?

Does the production method matter?







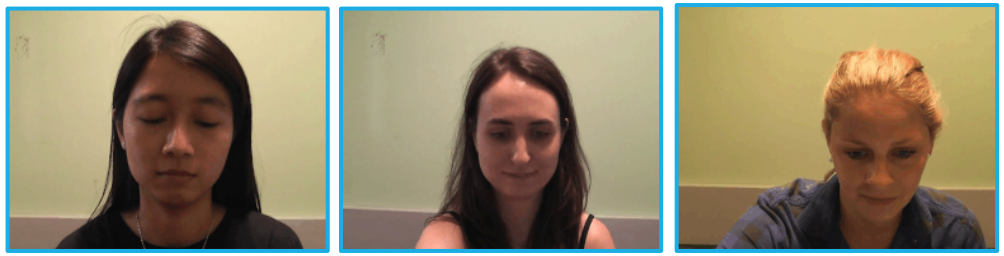


Kingston University London

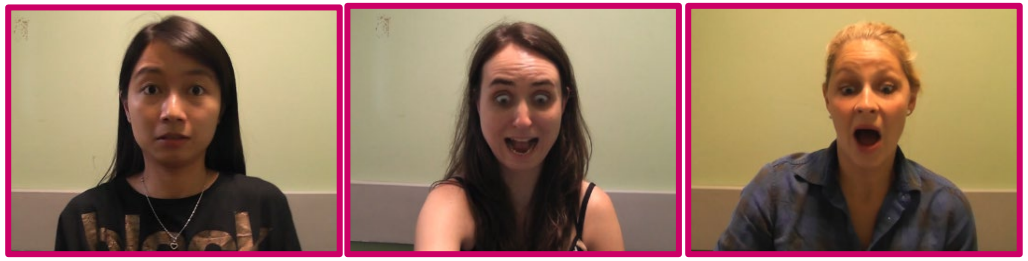
STIMULI CREATION (ZLOTEANU, ET AL., 2018; 2020)

PRESENTATION FORMAT

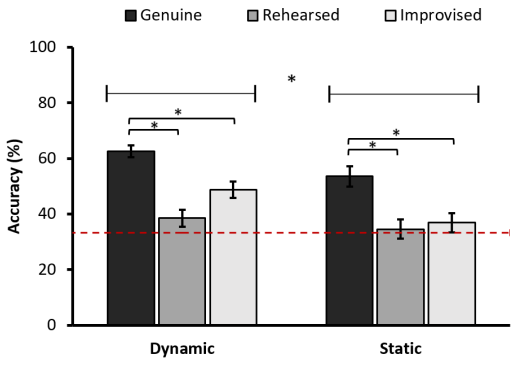
DYNAMIC VS STATIC EXPRESSIONS



VS

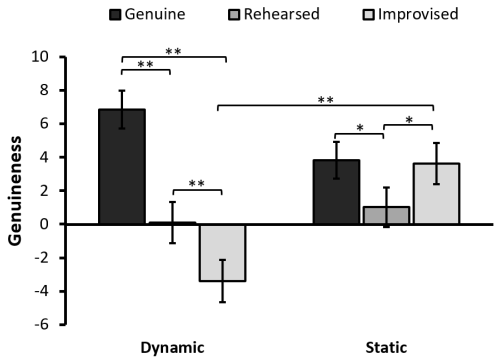


Dynamic > Static ($M_{diff} \approx 10\%$)



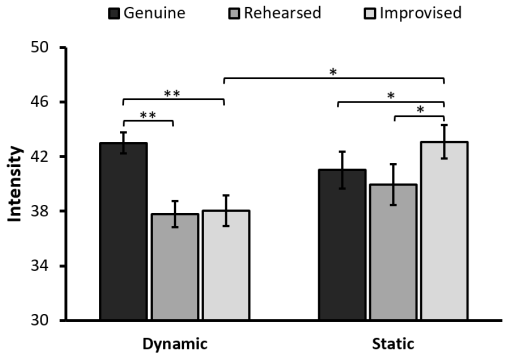
Dynamic v Static

Improvised$_D$ < Improvised$_S$



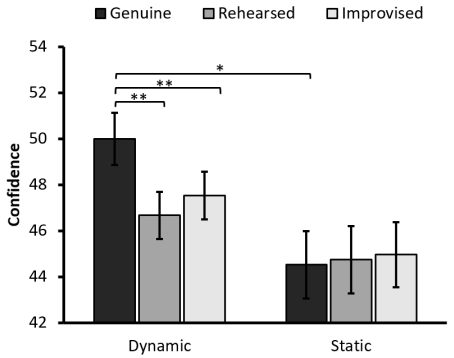
Dynamic v Static

Genuine$_D$ = Genuine$_S$

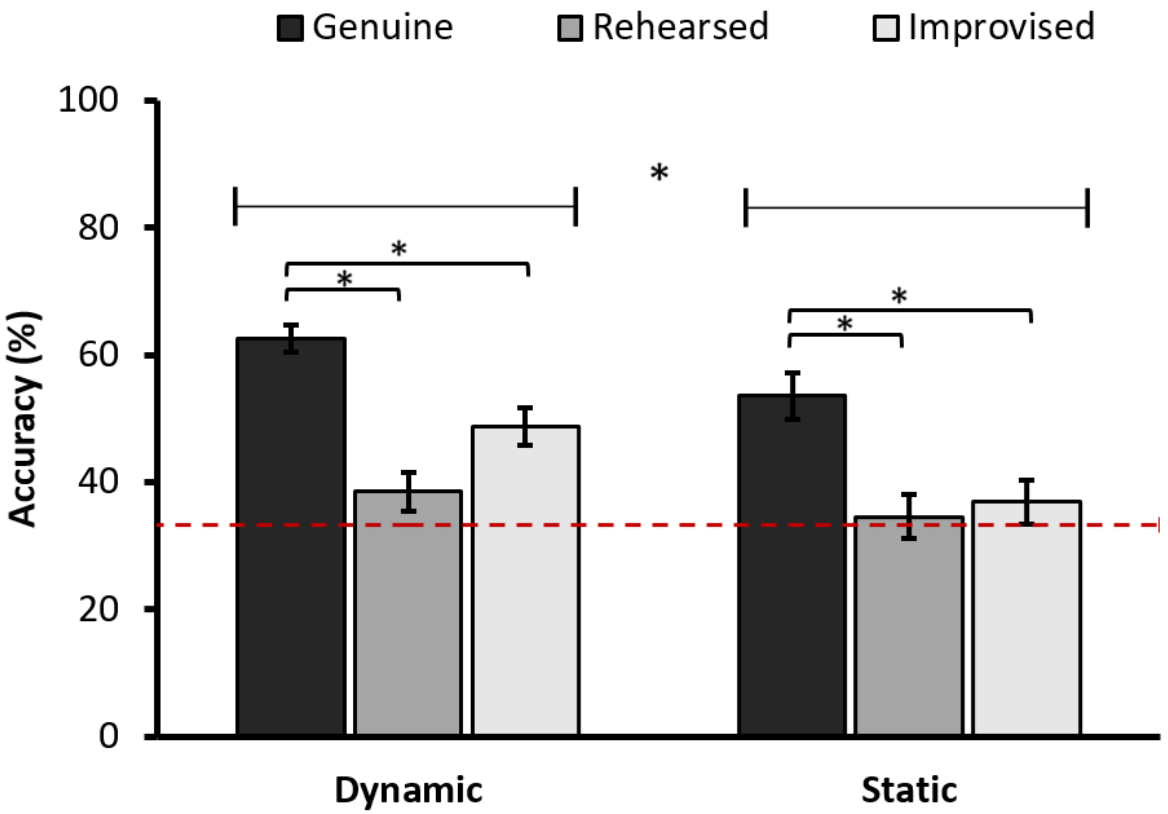


Dynamic v Static

Genuine$_D$ > Genuine$_S$



DISCRIMINATION ACCURACY



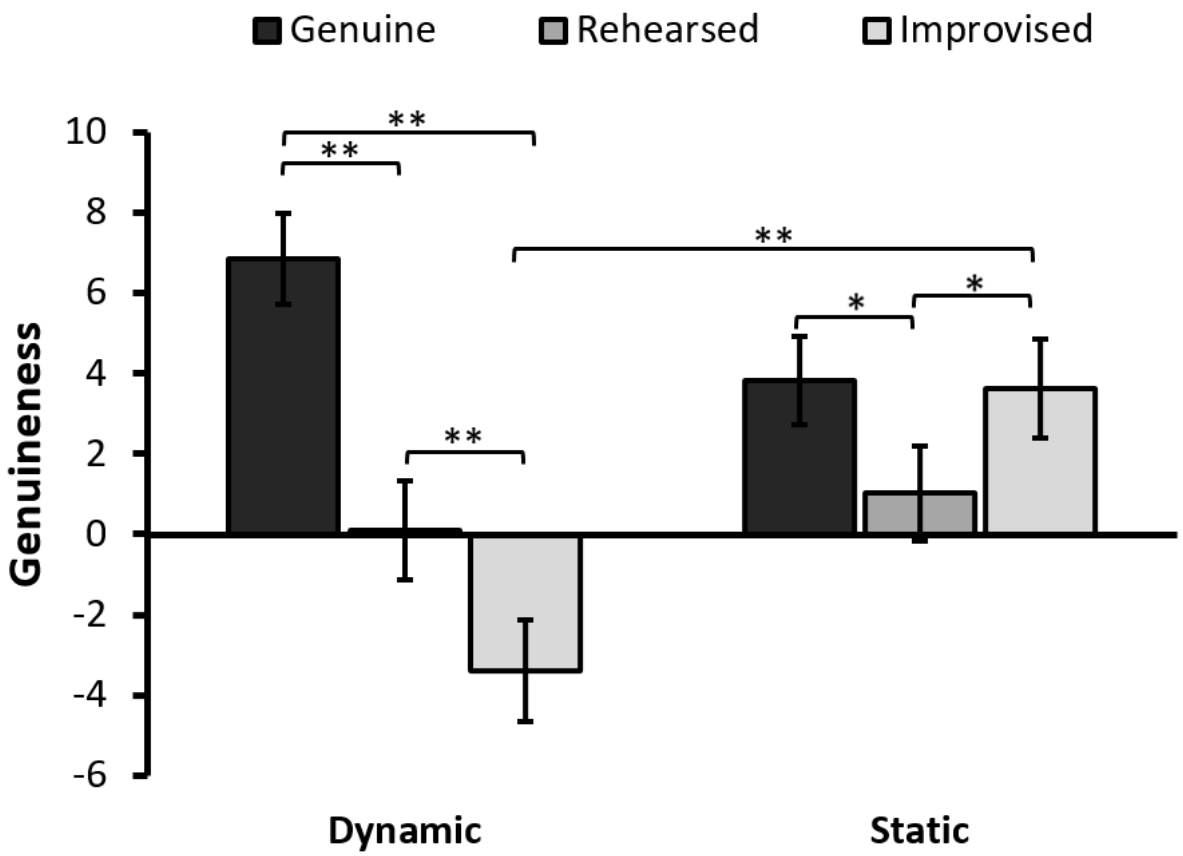
Presentation Format

- Dynamic > Static (≈ 10%)

Expression Condition:

- Genuine > Rehearsed = Improvised

GENUINENESS



Dynamic Condition:

- Genuine > Rehearsed | Improvised
- Improvised < Rehearsed

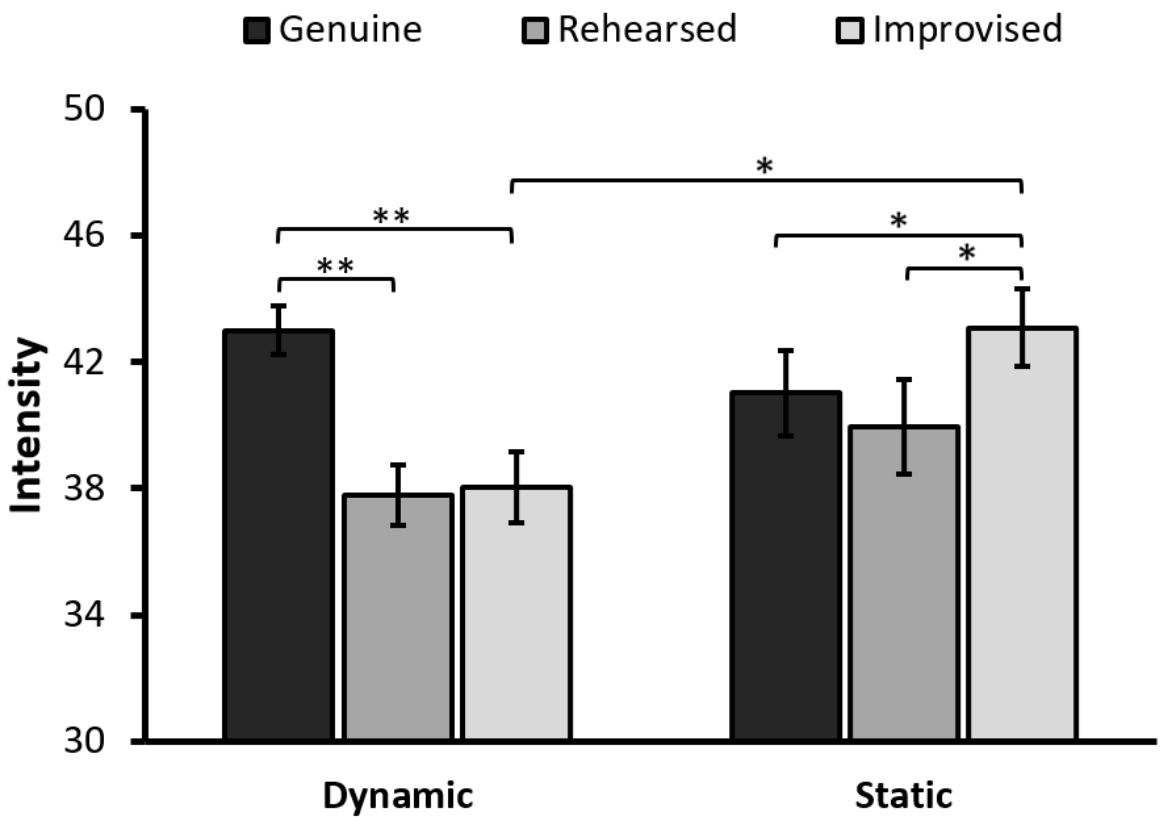
Static Condition:

- Genuine > Rehearsed
- Improvised > Rehearsed
- Genuine = Improvised

Dynamic v Static:

- Improvised Static < Improvised Dynamic
- Genuine Static = Genuine Dynamic
- Rehearsed Static = Rehearsed Dynamic

PERCEIVED INTENSITY



Dynamic condition

- Genuine > Rehearsed | Improvised
- Rehearsed = Improvised

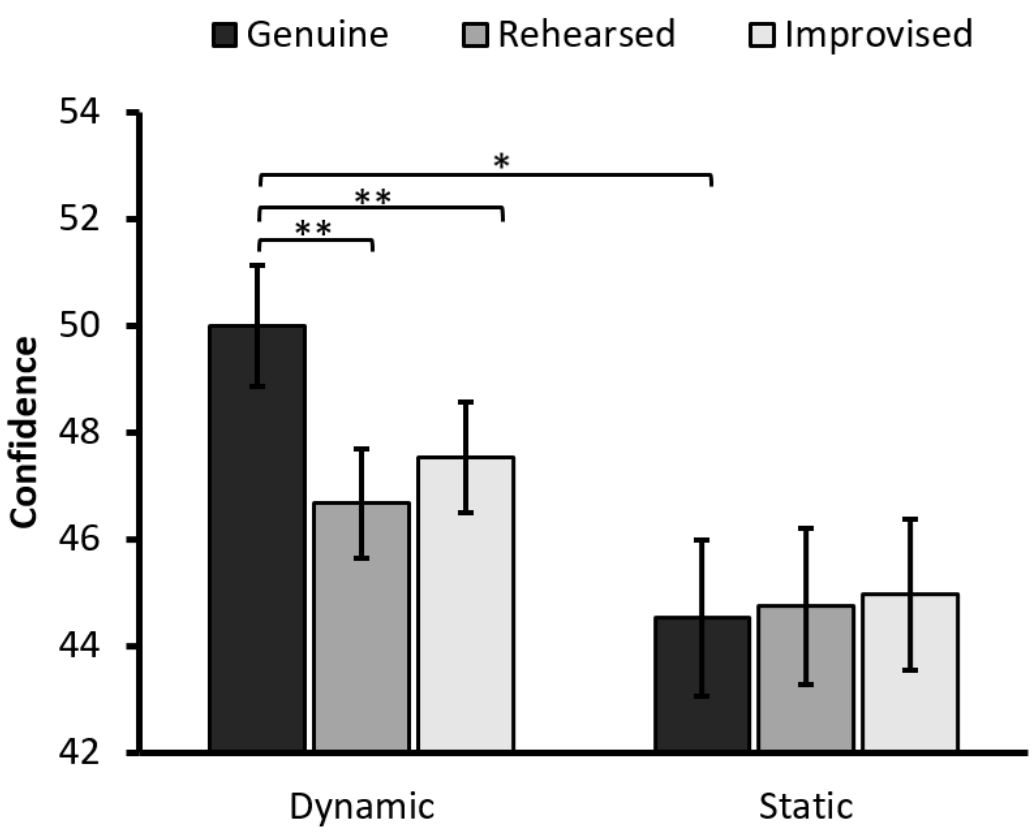
Static Condition

- Genuine < Improvised
- Genuine = Rehearsed
- Improvised > Rehearsed

Dynamic v Static

- $Improvised_{STATIC} > Improvised_{DYNAMIC}$

CONFIDENCE



Dynamic Condition

- Genuine > Rehearsed | Improvised
- Rehearsed = Improvised

Static Condition

- Genuine = Rehearsed = Improvised

Dynamic v Static

- Genuine > Genuine

FINDINGS

Accuracy: People are not great at discriminating dynamic expressions (60%)

And show an **authenticity bias** (assume most expressions are genuine)

Production Type matters: The type of deliberate expression affects (changes) judgement

Presentation Format matters: Expressions are judged differently if shown as static or dynamic stimuli

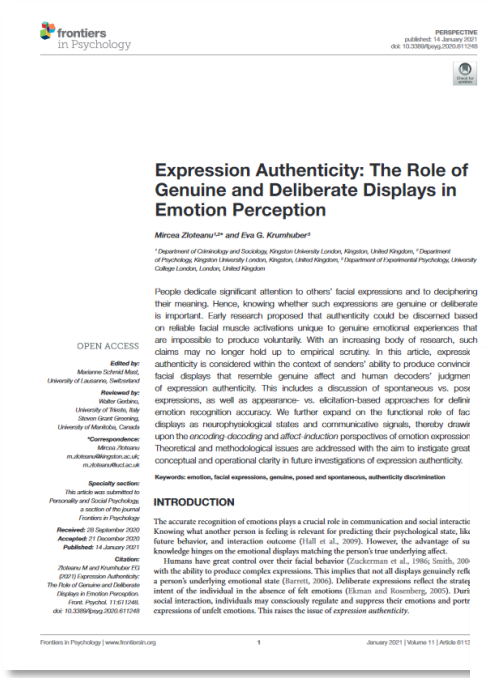
Now, imagine I didn't have 1x study with 4 conditions x 2 formats; I could have run 8x 2-condition (genuine/fake) studies. Each findings conflicting and contradictory results! The research community would be confused…

Kingston University London

IMPROVING EMOTION RESEARCH

WHAT CAUSED THIS?

- **Poor methodology**
  - Forced choice labels
  - Strong (unfounded and untested) assumptions
- **Lack of replication of core research and misinterpretation**
  - See Fridlund (1992; 1994)
- **Overreliance on pre-selected stimuli**
  - Turns emotion recognition into a "matching task"
- **Static and "prototypical" stimuli**
  - High intensity, clear, isolated, no contextual information, sole focus of task
- **Dichotomous thinking**
- **Incorrect analysis strategies**
  - No accounting for variability due to sender and receiver


frontiers in Psychology

PERSPECTIVE

Expression Authenticity: The Role of Genuine and Deliberate Displays in Emotion Perception


Evolutionary Human Sciences (2023), 4, e53, page 1 of 13

PERSPECTIVE

Darwin's illegitimate children: How body language experts undermine Darwin's legacy

OPERATIONAL DEFINITIONS

Defining your estimand & effects

- posed / deliberate / fake / deceptive / voluntary / non-genuine

- emotion *identification*, *categorization*, *discrimination*, *inference*, and *recognition*

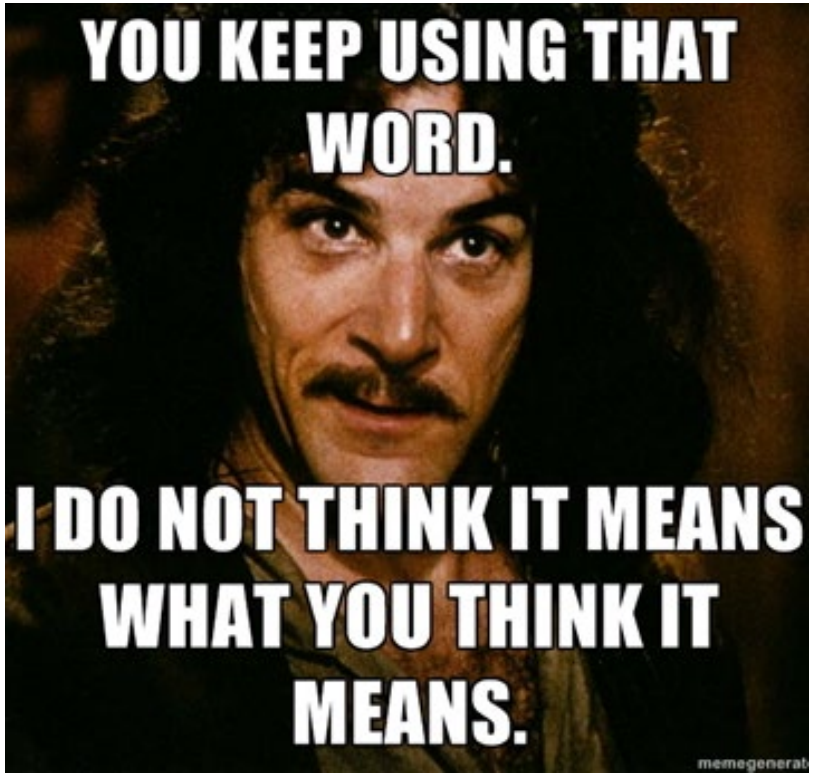
- Different terms for same thing & dame term for different things

  Zloteanu et al., (2020, 2018)

  - **emotion classification accuracy** is the ability to infer specific emotions from facial displays
  - **emotion authenticity discrimination** as the ability to differentiate between spontaneous (genuine) and posed (deliberate) displays.

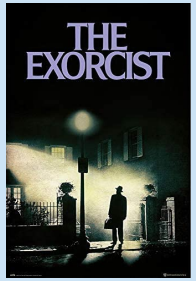
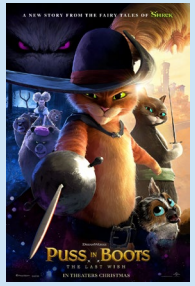
  Buck et al. (2017)

  - use the exact opposite definitions which they label **emotion categorization ability** and **emotion communication accuracy.**



BETTER MODELS: MIXED EFFECTS MODELS

ANOVAs treat all Trials/Senders as equivalent, but:

Video 1	Video 2	Video 3	Video 4
			

Not all the same, regardless of labels

ANOVAs treat all Participants as homogenous, but:

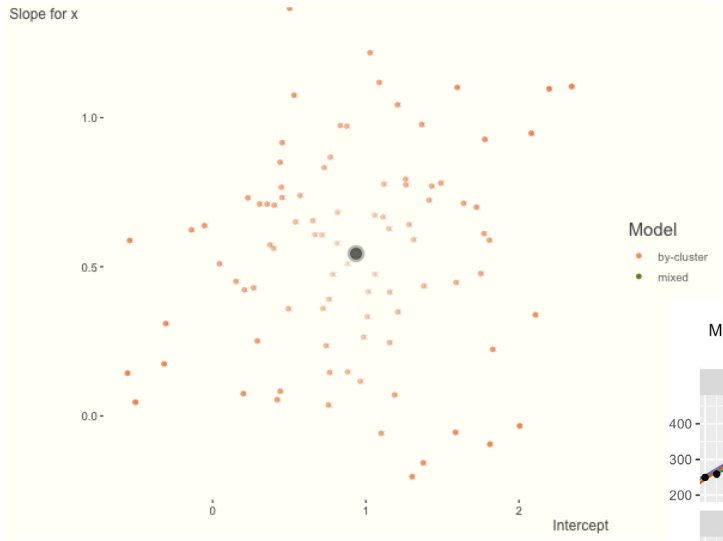
P 1	P 2	P 3	P 4
			

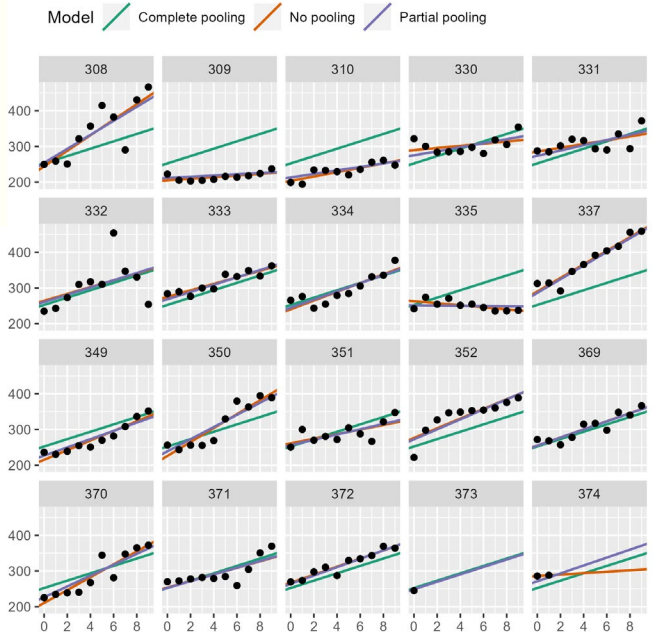
All response differences are ignored

WE CAN DO BETTER: BAYESIAN MIXED EFFECTS MODELS

Advantages over RM-ANOVA

- Same results as ANOVA analyses
- All data types permitted
- Complex designs
- Missing data
- Differing number of repeats (unbalanced data)





STREAMLINE OUR ANALYSES: 1 (SDT) MODEL!

Accuracy %

Within Subjects Effects

Cases	Sum of	df		F	p
Veracity		1		74.413	< .001
Veracity ✻ Condition		2		0.511	0.602
Residuals		103			

Note. Type III Sum of Sq

Between Subjects Eff

Cases	Sum	df	Mean Square	F	p
Condition		2	5.230	1.700	0.188
Residuals		103	3.076		

Note. Type III Sum

SDT – Acc

ANOVA - BDS_Aprime

Cases	Sum of Squares	df	uare	F	p
Condition	0.102	2		1.433	0.243
Residuals	3.655	103			

Note. Type III Sum of Squares

s

ANOVA - BDS_Bias

Cases	Sum of	df	Mean Square	F	p
Condition	17	2	8.600	0.511	0.602
Residuals	1734.53		16.840		

Note. Type III Sum of Squares

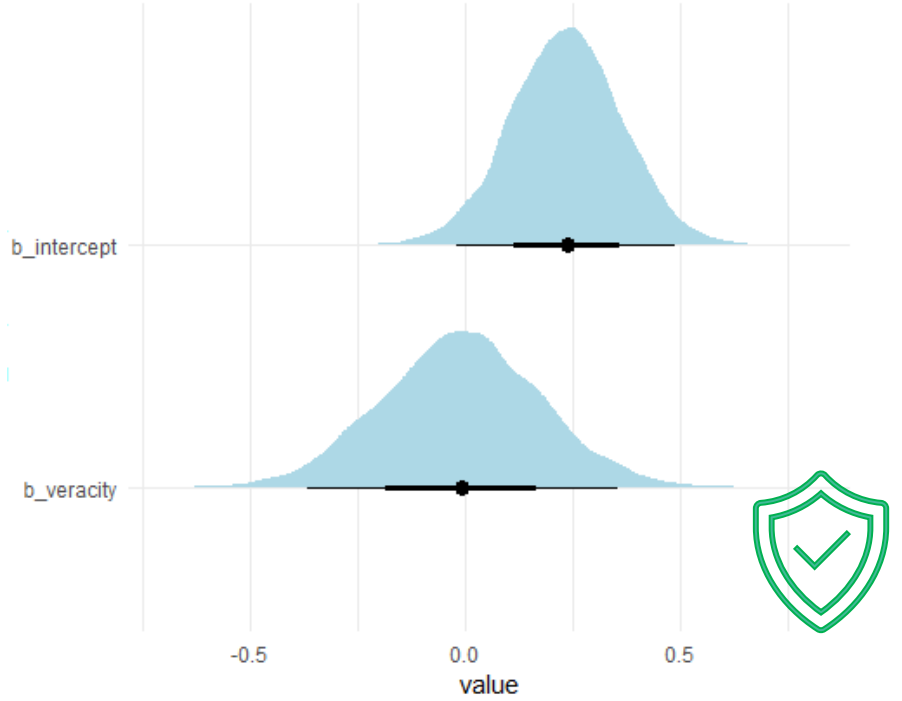
T – Bias (c)

ANOVA - BDS_b2

Cases	Sum	df	Me	F	p
Condition	0.	2	3	0.617	0.541
Residuals	13.906		.135		

Note. Type III Sum of Squares

https://doi.org/10.13140/RG.2.2.24441.13926 for Talk
https://osf.io/abts4/ for R script



Summary of Posterior Distribution

Parameter	Median	95% CI	pd	ROPE	% in ROPE
(Intercept)	0.24	[-0.02, 0.49]	96.53%	[-0.10, 0.10]	12.47%
Veracity	-6.44e-03	[-0.37, 0.36]	51.32%	[-0.10, 0.10]	44.58%

EXAMPLE FOR "ACCURACY": PROBIT MODELS

Data Preparation

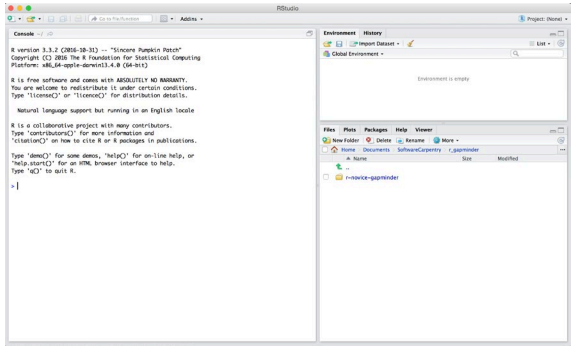
Long format

	A	B	C	D	E
1	Participan	Stimuli	Veracity	Answer	Condition
2	1	video1L	1	1	ERT
3	1	video2L	0	0	ERT
4	1	video3T	0	1	ERT
5	1	video4T	1	1	ERT
6	2	video1L	0	0	BT
7	2	video2L	0	1	BT
8	2	video3T	1	1	BT
9	2	video4T	0	1	BT
10	3	video1L	0	1	CT
11	3	video2L	1	0	CT
12	3	video3T	0	1	CT
13	3	video4T	1	1	CT

Truth = 1
Lie = 0

R package

```
library(brms)
library(bayestestR)
library(emmeans)
```



Bayesian Priors

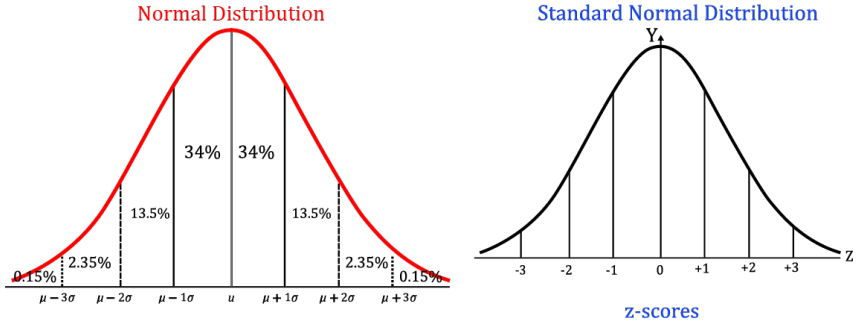
As the probit CDF back-transforms to a Z-curve, we can see the parameter space the same as a Normal distribution with mean = 0, and SD = 1.

So, think in terms of Cohen's d!

Some acceptable priors for the coefficients is N ~ (0,1)

But, avoid being too specific for interactions.

Note, overall priors matter most of *model convergence* issues or computing *Bayes Factors*



PROBIT MODELS

Syntax

d'

-c

Participant variance

Video variance

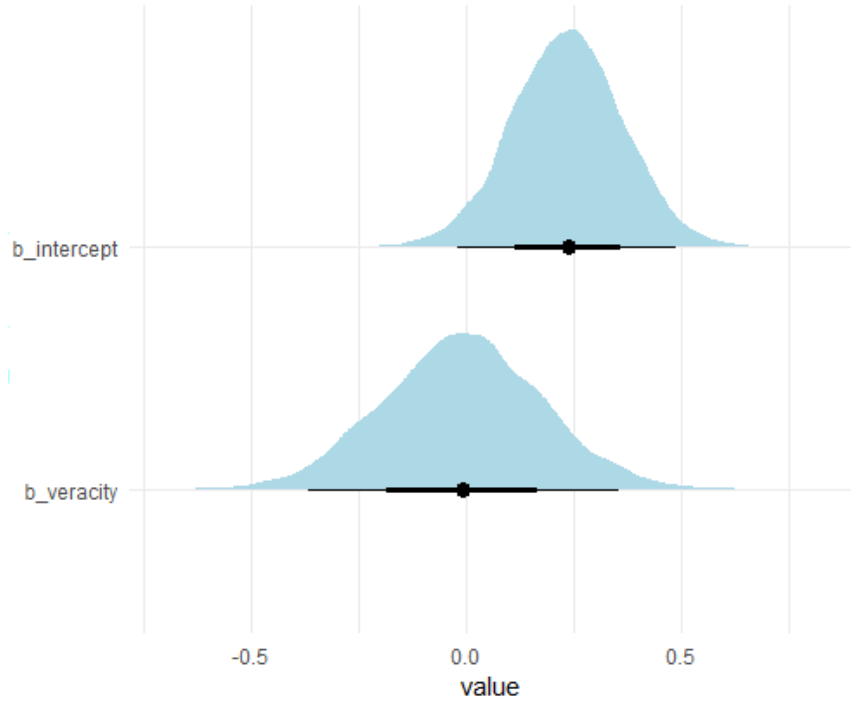
```
m1 <- brm(Answer ~ 1 + Veracity + (1 + Veracity | Participant) + (1 | Stimuli),
          data = my_data,
          family = bernoulli(link = probit)
          )
```

Output

```
Summary of Posterior Distribution

Parameter   |    Median |         95% CI |     pd |          ROPE | % in ROPE |
-------------------------------------------------------------------------------
(Intercept) |      0.24 | [-0.02, 0.49] | 96.53% | [-0.10, 0.10] |    12.47% |
Veracity    | -6.44e-03 | [-0.37, 0.36] | 51.32% | [-0.10, 0.10] |    44.58% |
```

Plots

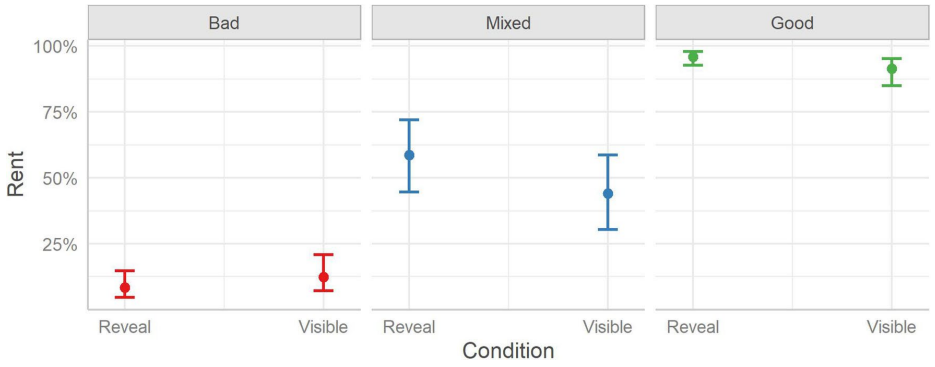


ALL DATA-TYPES WELCOME!

Categorical

Syntax

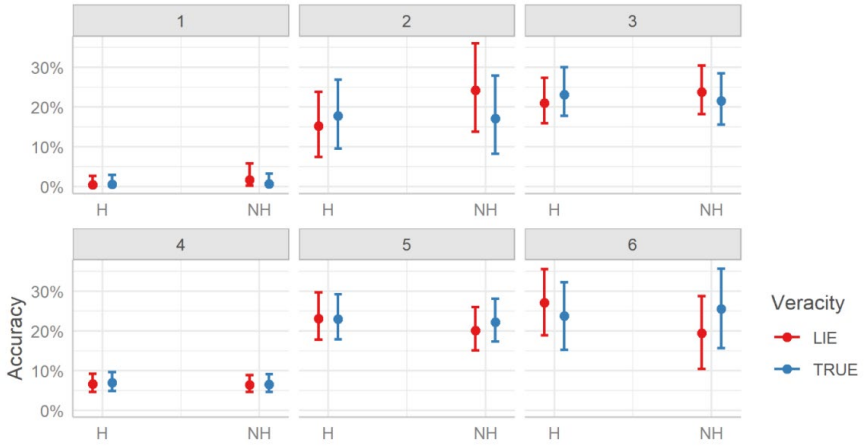
```
m2 <- brm(Answer ~ 1 + Veracity + (1 + Veracity | Participant)
+ (1 | Stimuli),
          data = my_data,
          family = categorical()
          )
```



Ordinal (Likert, scale)

Syntax

```
m3 <- brm(Answer ~ 1 + Veracity + (1 + Veracity | Participant)
+ (1 | Stimuli),
          data = my_data,
          family = cumulative()
          )
```



Kingston University London

OPEN SCIENCE

OPEN RESEARCH

Reproducible

- Share your analysis code

Open

- Make your data public
- Share your videos!!!

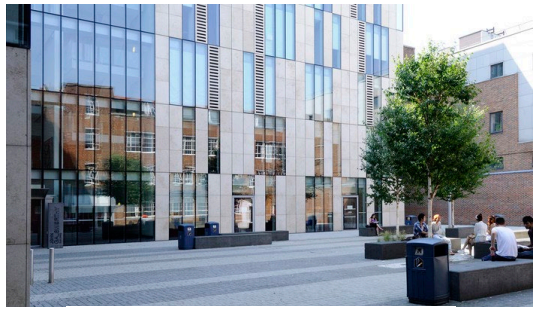
Interpretable

- Use estimation language
- Report effect sizes in different ways
- Plot your data

Transparent

- Pre-register your study!
- Differentiate Planned from Exploratory analyses

SHARING IS CARING (AND NECESSARY FOR SCIENTIFIC INTEGRITY)

LAB 1	LAB 2	LAB 3
		
		
There IS a difference & it's POSITIVE!	There's NO difference!	There IS a difference & but it's NEGATIVE

MANY FACES PROJECT

A big team science approach to face perception and recognition

https://osf.io/ngjq7/

TAKE AWAY MESSAGES

FINAL THOUGHTS

Pick a framework (or invent your own)

Be specific on what you believe – what are your assumptions?

Figure out what effects in your area look like and what you expect to find

Make specific, testable, and falsifiable predictions (see also *severe testing*)

Share your data, code, stimuli, papers

Engage in debates and discussions

Don't be afraid to be wrong!

(oh, and use Bayesian Mixed effects models!)

THANK YOU!

QUESTIONS?

Contact

: m.zloteanu@kingston.ac.uk

: @mzloteanu

: mz555.github.io