



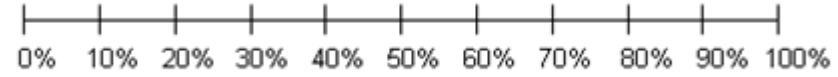
**University of
Zurich** ^{UZH}

A HIERARCHICAL BAYESIAN IMPLEMENTATION OF PURELY BAYESIAN AND BAYESIAN MIXTURE MODELS OF CONDITIONAL REASONING

Henrik Singmann

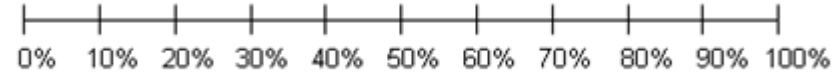
A girl had sexual intercourse.

How likely is it that the girl is pregnant?



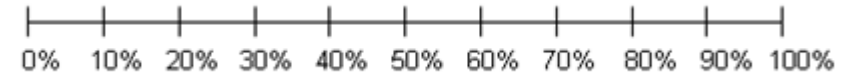
A girl had sexual intercourse.

How likely is it that the girl is pregnant?



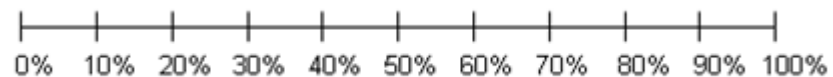
A girl is NOT pregnant.

How likely is it that the girl had NOT had sexual intercourse?



A girl had sexual intercourse.

How likely is it that the girl is pregnant?



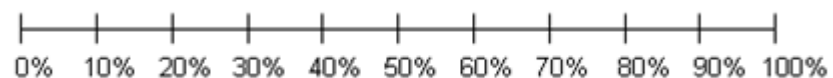
A girl is NOT pregnant.

How likely is it that the girl had NOT had sexual intercourse?



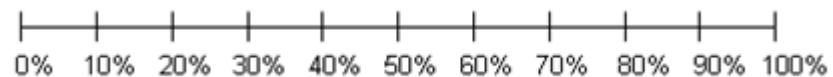
A girl is pregnant.

How likely is it that the girl had sexual intercourse?



A girl had sexual intercourse.

How likely is it that the girl is pregnant?



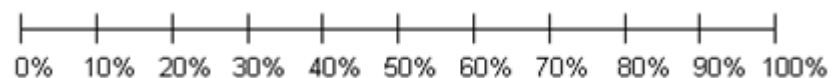
A girl is NOT pregnant.

How likely is it that the girl had NOT had sexual intercourse?



A girl is pregnant.

How likely is it that the girl had sexual intercourse?



A girl had NOT had sexual intercourse.

How likely is it that the girl is NOT pregnant?



A girl had sexual intercourse.

How likely is it that the girl is pregnant?



A girl is NOT pregnant.

How likely is it that the girl had NOT had sexual intercourse?



A girl is pregnant.

How likely is it that the girl had sexual intercourse?



A girl had NOT had sexual intercourse.

How likely is it that the girl is NOT pregnant?



If a girl has sexual intercourse then she will be pregnant.

A girl had sexual intercourse.

How likely is it that the girl is pregnant?



A girl had sexual intercourse.

How likely is it that the girl is pregnant?



A girl is NOT pregnant.

How likely is it that the girl had NOT had sexual intercourse?



A girl is pregnant.

How likely is it that the girl had sexual intercourse?



A girl had NOT had sexual intercourse.

How likely is it that the girl is NOT pregnant?



If a girl has sexual intercourse then she will be pregnant.

A girl had sexual intercourse.

How likely is it that the girl is pregnant?



If a girl has sexual intercourse then she will be pregnant.

A girl is NOT pregnant.

How likely is it that the girl had NOT had sexual intercourse?



A girl had sexual intercourse.

How likely is it that the girl is pregnant?



A girl is NOT pregnant.

How likely is it that the girl had NOT had sexual intercourse?



A girl is pregnant.

How likely is it that the girl had sexual intercourse?



A girl had NOT had sexual intercourse.

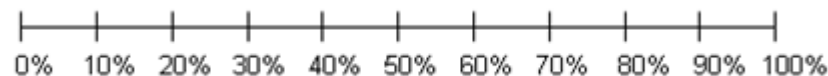
How likely is it that the girl is NOT pregnant?



If a girl has sexual intercourse then she will be pregnant.

A girl had sexual intercourse.

How likely is it that the girl is pregnant?



If a girl has sexual intercourse then she will be pregnant.

A girl is NOT pregnant.

How likely is it that the girl had NOT had sexual intercourse?



If a girl has sexual intercourse then she will be pregnant.

A girl is pregnant.

How likely is it that the girl had sexual intercourse?



A girl had sexual intercourse.

How likely is it that the girl is pregnant?



A girl is NOT pregnant.

How likely is it that the girl had NOT had sexual intercourse?



A girl is pregnant.

How likely is it that the girl had sexual intercourse?



A girl had NOT had sexual intercourse.

How likely is it that the girl is NOT pregnant?



If a girl has sexual intercourse then she will be pregnant.

A girl had sexual intercourse.

How likely is it that the girl is pregnant?



If a girl has sexual intercourse then she will be pregnant.

A girl is NOT pregnant.

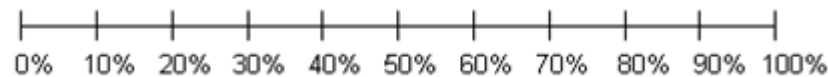
How likely is it that the girl had NOT had sexual intercourse?



If a girl has sexual intercourse then she will be pregnant.

A girl is pregnant.

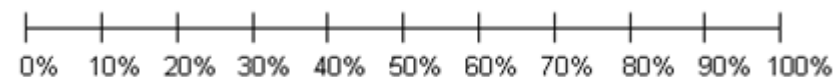
How likely is it that the girl had sexual intercourse?



If a girl has sexual intercourse then she will be pregnant.

A girl had NOT had sexual intercourse.

How likely is it that the girl is NOT pregnant?



A girl had sexual intercourse.

How likely is it that the girl is pregnant?



A girl is NOT pregnant.

How likely is it that the girl had NOT had sexual intercourse?



Experimental paradigm:

- 1. Session: Reduced inferences (no conditional)
- 2. Session: Full conditional inferences
- 4 different conditionals (i.e., contents)
- Participants respond to all 4 inferences per session and content.

A girl is pregnant.

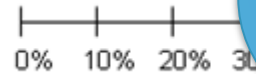
How likely is it that the



If a girl has sexual inter

A girl had sexual inter

How likely is it that the

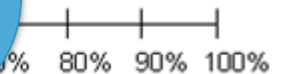


ant?



will be pregnant.

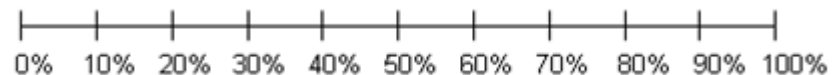
sexual intercourse?



If a girl has sexual intercourse then she will be pregnant.

A girl is pregnant.

How likely is it that the girl had sexual intercourse?



If a girl has sexual intercourse then she will be pregnant.

A girl had NOT had sexual intercourse.

How likely is it that the girl is NOT pregnant?



RESULTS

N = 101

Klauer, Beller, & Hütter (2010, Exp. 1)

Singmann, Klauer, & Beller (2016, Exp. 1 & 3)

Balloon: If a balloon is pricked with a needle then it will pop.

- few disablers, many alternatives

Coke: If a person drinks a lot of coke then the person will gain weight.

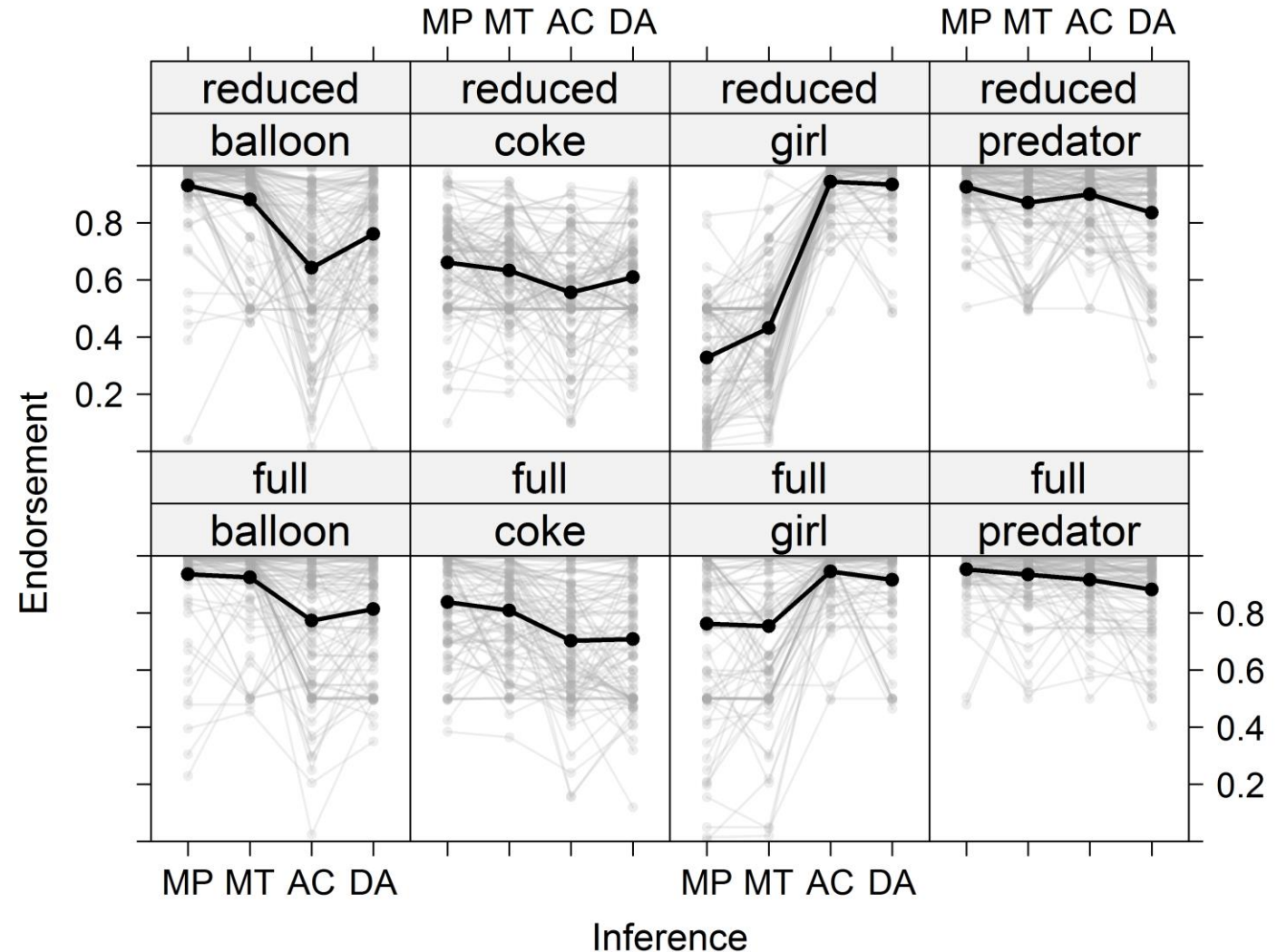
- many disablers, many alternatives

Girl: If a girl has sexual intercourse then she will be pregnant.

- many disablers, few alternatives

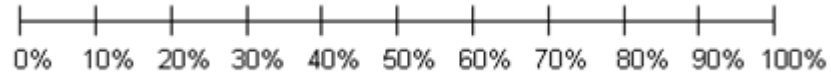
Predator: If a predator is hungry then it will search for prey.

- few disablers, few alternatives



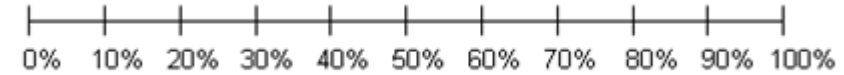
A girl had sexual intercourse.

How likely is it that the girl is pregnant?



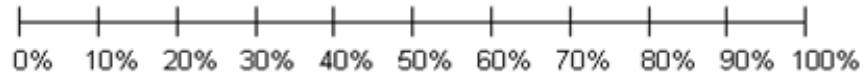
A girl is NOT pregnant.

How likely is it that the girl had NOT had sexual intercourse?



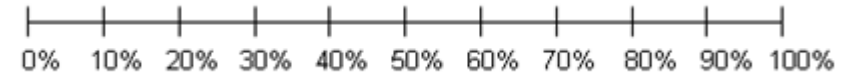
A girl is pregnant.

How likely is it that the girl had sexual intercourse?



A girl had NOT had sexual intercourse.

How likely is it that the girl is NOT pregnant?



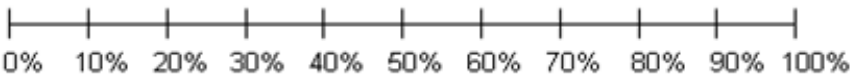
A girl had sexual intercourse.
How likely is it that the girl is pregnant?



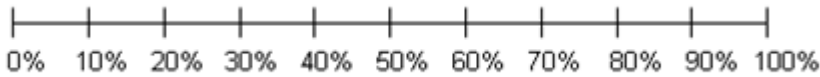
A girl is NOT pregnant.
How likely is it that the girl had NOT had sexual intercourse?



A girl is preg
How likely is



se.
regnant?



Inference	"MP"	"MT"	"AC"	"DA"
	p $\therefore q$	$\neg q$ $\therefore \neg p$	q $\therefore p$	$\neg p$ $\therefore \neg q$
Response reflects	$P(q p)$	$P(\neg p \neg q)$	$P(p q)$	$P(\neg q \neg p)$

A girl had sexual intercourse.

How likely is it that the girl is pregnant?

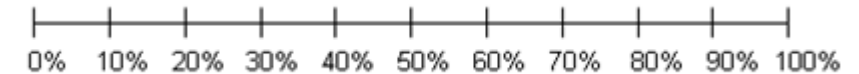
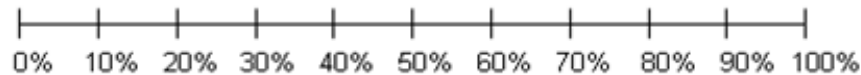


A girl is NOT pregnant.

How likely is it that the girl had NOT had sexual intercourse?



Inference	"MP"	"MT"	"AC"	"DA"
	p $\therefore q$	$\neg q$ $\therefore \neg p$	q $\therefore p$	$\neg p$ $\therefore \neg q$
Response reflects	$P(q p)$	$P(\neg p \neg q)$	$P(p q)$	$P(\neg q \neg p)$



Joint probability distribution $F_{p,q}$		
	q	$\neg q$
p	$P(p \wedge q)$	$P(p \wedge \neg q)$
$\neg p$	$P(\neg p \wedge q)$	$P(\neg p \wedge \neg q)$

3 free parameters

Provides conditional probabilities/predictions:

- $P(\text{MP}) = P(q | p) = P(p \wedge q) / P(p)$
- $P(\text{MT}) = P(\neg p | \neg q) = P(\neg p \wedge \neg q) / P(\neg q)$
- $P(\text{AC}) = P(p | q) = P(p \wedge q) / P(q)$
- $P(\text{DA}) = P(\neg q | \neg p) = P(\neg p \wedge \neg q) / P(\neg p)$

Oaksford, Chater, & Larkin (2000)

Oaksford & Chater (2007)

HIERARCHICAL MODELING

2 classical approaches for dealing with individual differences:

- *complete pooling*: ignores individual variability
- *no pooling*: ignores similarity across participants (e.g., Oaksford, Chater, & Larkin, 2000; Klauer, Beller, & Hütter, 2010; Singmann, Klauer, & Beller, 2016)

Partial pooling principled alternative:

- Individual level parameters are drawn from group-level distributions
- Provides higher precision for parameter estimates (even on the individual level)

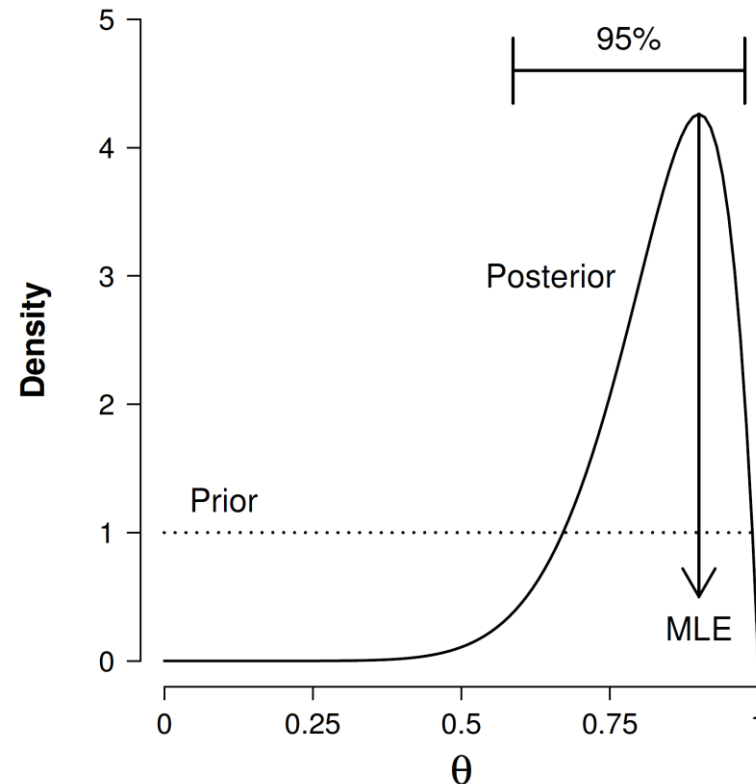


BAYESIAN STATISTICS

Requires likelihood (i.e., no least squares).

Information (uncertainty) regarding parameters expressed via (continuous) probability distributions.

1. *Prior distributions* capture ignorance before data is collected.
2. Prior distributions *updated* in light of data using *Bayes' theorem*.
3. *Posterior distributions* reflect new state of knowledge.



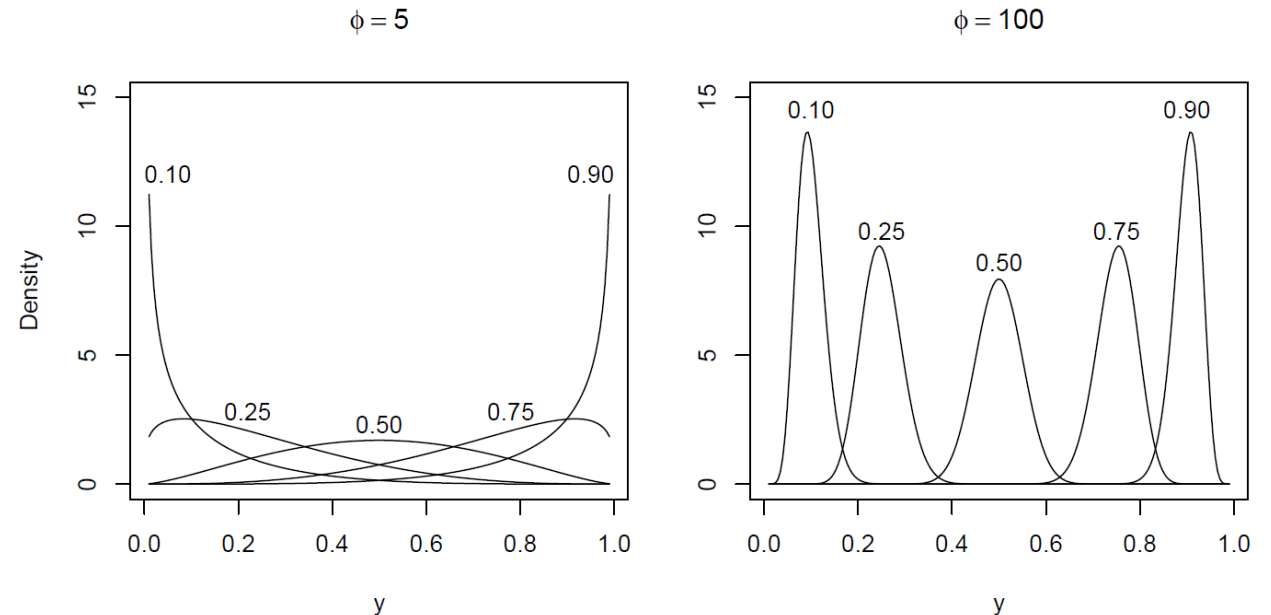
BETA REGRESSION

Allows to model data in unit interval $(0, 1)$ using beta distribution.

Instead of shape parameters α and β , uses mean μ and precision ϕ :

- $\alpha = \mu\phi$
- $\beta = (1 - \mu)\phi$

Naturally addresses heteroscedasticity: More variation in mid ranges than at the upper and lower end.



HYPERDISTRIBUTION FOR PROBABILITY DISTRIBUTION

Predictions of Bayesian model result from probability distribution $F_{p,q}$.

Oaksford and Chater parameterize $F_{p,q}$ using three parameters:

- $a = P(p)$
- $b = P(q)$
- $e = P(\text{not-}q | p) = 1 - P(q | p)$

Not all values of a , b , and e result in proper probability distribution:

- e is bound: $[\max(\frac{a-b}{a}, 0), \min(\frac{1-b}{a}, 1)]$

The joint distribution of a , b , and e cannot be a proper hyper/prior distribution for $F_{p,q}$.

Alternative provided by Dirichlet distribution, which usually has 2 parameters:

- $K \geq 2$, number of categories (integer)
- $\alpha_1, \dots, \alpha_K$, concentration parameter

Support over K -dimensional vectors that sum to 1 (i.e., $(K - 1)$ -dimensional simplex).

Parameterization as in beta-regression possible (e.g., Kemp, Perfors, & Tenenbaum, 2007):

- γ : mean of hyperparameter
- ψ : precision of hyperparameter

HIERARCHICAL BAYESIAN MODEL

(simple model)

Data: $E_{\text{red},ijk} \sim \text{Beta}(\alpha_{\text{red},ijk}, \beta_{\text{red},ijk})$

Group-level distribution: $F_{p,q,jk} \sim \text{Dirichlet}(\gamma_j \times \psi_j)$

Priors:

$$\gamma_j \sim \text{Dirichlet}(1)$$

$$\psi_j \sim \text{Cauchy}^+(1, 25)$$

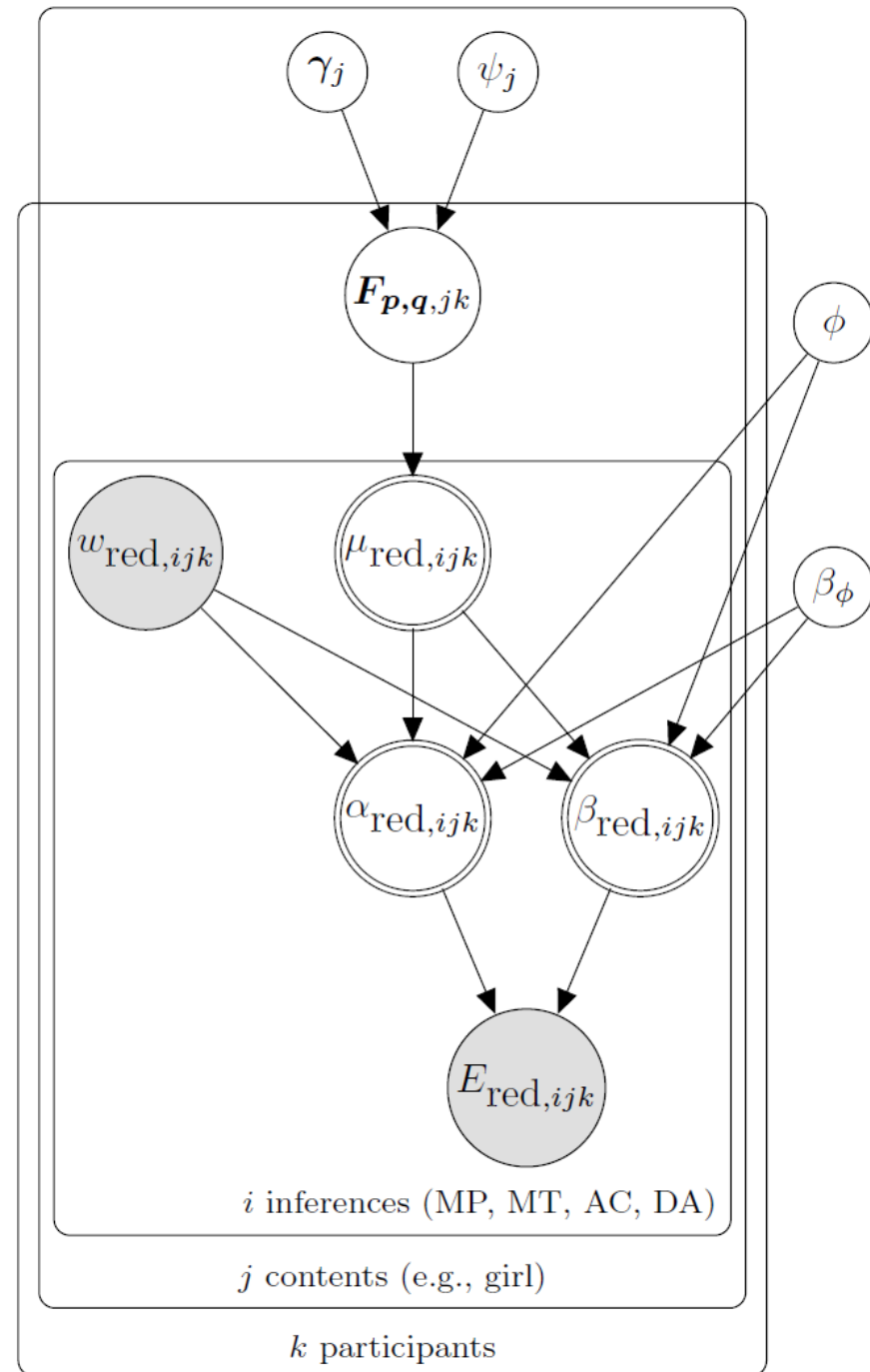
$$\phi \sim \text{Cauchy}^+(2, 25)$$

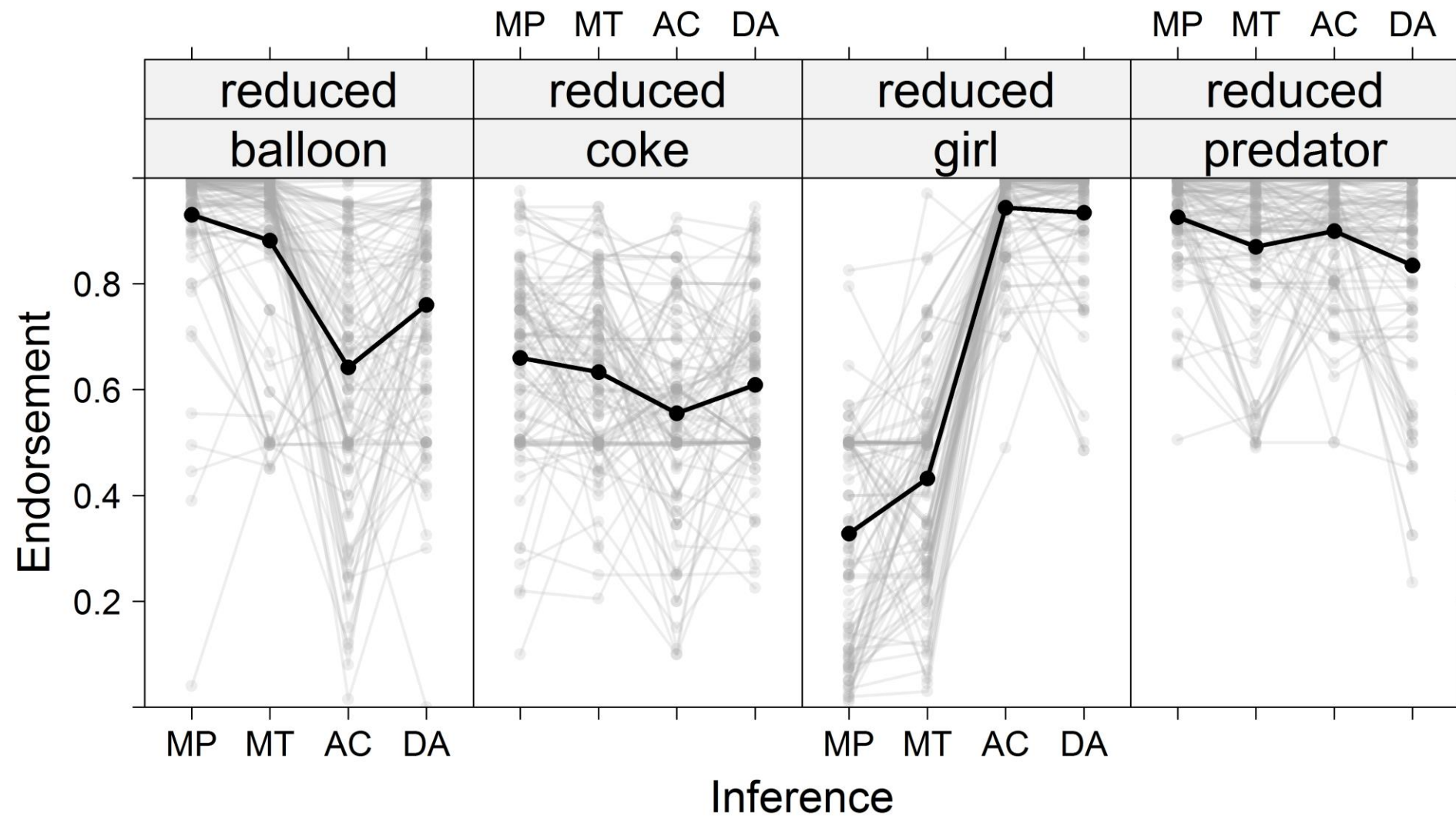
$$\beta_\phi \sim \text{Cauchy}^+(0, 25)$$

Beta regression:

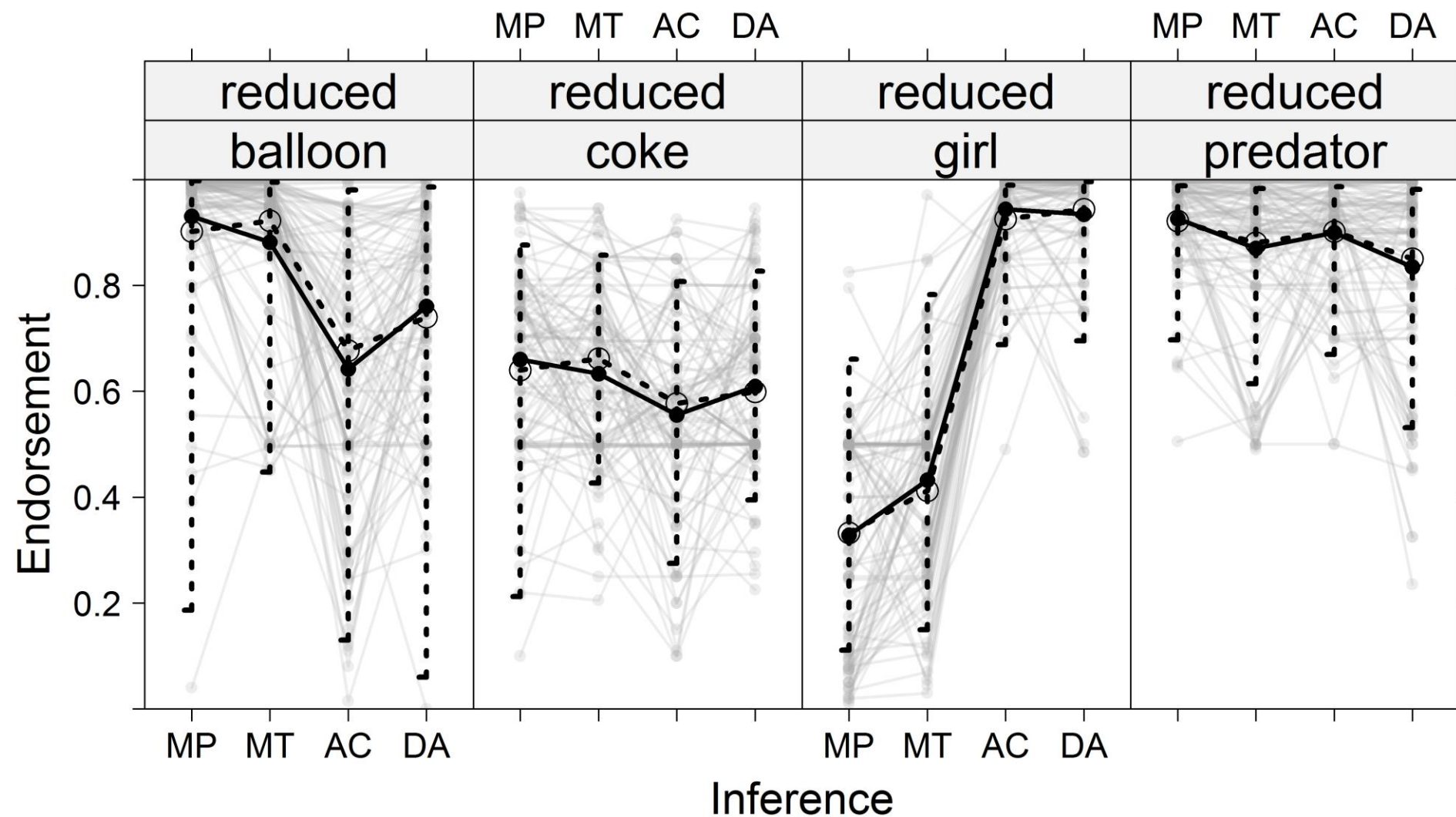
$$\alpha = \mu \times (\phi + \beta_\phi w)$$

$$\beta = (1 - \mu) \times (\phi + \beta_\phi w)$$

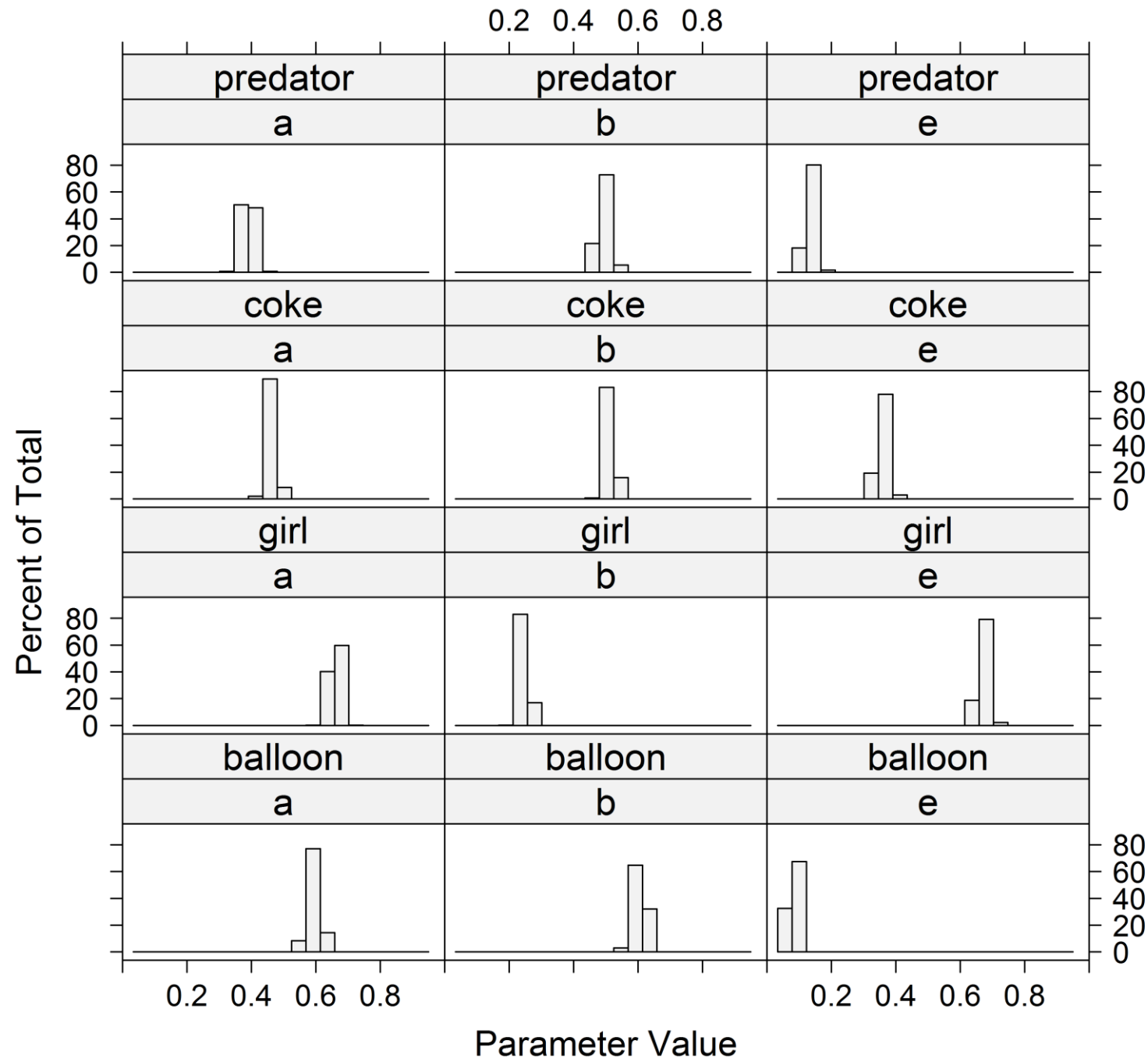




Simple model:



Black error bars: Range of individual level predictions from simple model



Balloon: If a balloon is pricked with a needle then it will pop.

- few disablers, many alternatives

Coke: If a person drinks a lot of coke then the person will gain weight.

- many disablers, many alternatives

Girl: If a girl has sexual intercourse then she will be pregnant.

- many disablers, few alternatives

Predator: If a predator is hungry then it will search for prey.

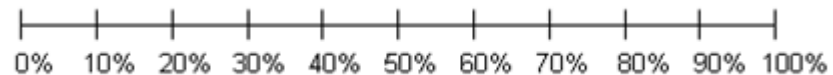
- few disablers, few alternatives

EXPERIMENTAL PARADIGM

Reduced Inferences (Week 1)

A girl had sexual intercourse.

How likely is it that the girl is pregnant?

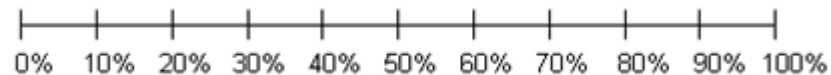


EXPERIMENTAL PARADIGM

Reduced Inferences (Week 1)

A girl had sexual intercourse.

How likely is it that the girl is pregnant?



Full Inferences (Week 2+)

If a girl had sexual intercourse, then she is pregnant.

A girl had sexual intercourse.

How likely is it that the girl is pregnant?



EXPERIMENTAL PARADIGM

ences (Week 2+)

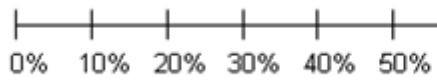
al intercourse, then she

is pregnant.

A girl had sexual intercourse.

A girl had sexual intercourse.

How likely is it that th



Inference	"MP"	"MT"	"AC"	"DA"
	p $\therefore q$	$\neg q$ $\therefore \neg p$	q $\therefore p$	$\neg p$ $\therefore \neg q$
Response reflects	$P(q p)$	$P(\neg p \neg q)$	$P(p q)$	$P(\neg q \neg p)$

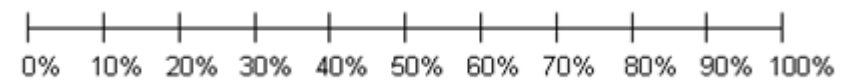
Inference	MP	MT	AC	DA
	$p \rightarrow q$ p $\therefore q$	$p \rightarrow q$ $\neg q$ $\therefore \neg p$	$p \rightarrow q$ q $\therefore p$	$p \rightarrow q$ $\neg p$ $\therefore \neg q$
Response reflects	$P(q p)$	$P(\neg p \neg q)$	$P(p q)$	$P(\neg q \neg p)$

BAYESIAN UPDATING

Reduced Inferences (Week 1)

A girl had sexual intercourse.

How likely is it that the girl is pregnant?

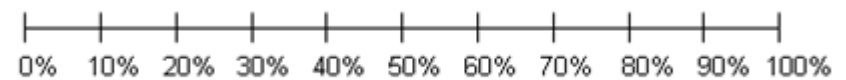


Full Inferences (Week 2)

If a girl had sexual intercourse, then she is pregnant.

A girl had sexual intercourse.

How likely is it that the girl is pregnant?



Joint probability distribution: $F_{p,q}$

	q	$\neg q$
p	$P(p \wedge q)$	$P(p \wedge \neg q)$
$\neg p$	$P(\neg p \wedge q)$	$P(\neg p \wedge \neg q)$

Updated joint probability distribution: $F_{p,q}'$

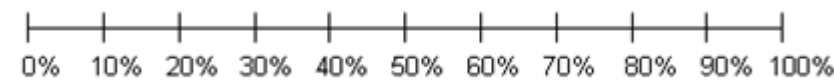
	q'	$\neg q'$
p'	$P(p' \wedge q')$	$P(p' \wedge \neg q')$
$\neg p'$	$P(\neg p' \wedge q')$	$P(\neg p' \wedge \neg q')$

BAYESIAN UPDATING

Reduced Inferences (Week 1)

A girl had sexual intercourse.

How likely is it that the girl is pregnant?

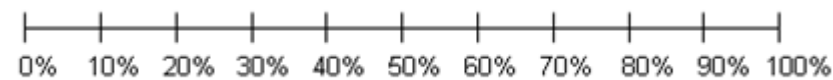


Full Inferences (Week 2)

If a girl had sexual intercourse, then she is pregnant.

A girl had sexual intercourse.

How likely is it that the girl is pregnant?



Joint probability distribution: $F_{p,q}$

	q	$\neg q$
p	$P(p \wedge q)$	$P(p \wedge \neg q)$
$\neg p$	$P(\neg p \wedge q)$	$P(\neg p \wedge \neg q)$

?

Updated joint probability distribution: $F_{p,q}'$

	q'	$\neg q'$
p'	$P(p' \wedge q')$	$P(p' \wedge \neg q')$
$\neg p'$	$P(\neg p' \wedge q')$	$P(\neg p' \wedge \neg q')$

BAYESIAN UPDATING

Reduced Inferences (Week 1)

Full Inferences (Week 2)

If a girl had sexual intercourse, then she

Role of conditional in Bayesian models:

- *PROB*: increases probability of conditional, $P(q | p)$ (Oaksford et al., 2000): $e' < e$
- *EX-PROB*: increases probability of conditional $P_{MP}(q | p) > P_{other}(q | p)$ (Oaksford & Chater, 2007)
- *KL*: increases $P(q | p)$ & Kullback-Leibler distance between $F_{p,q}$ and $F_{p,q}'$ is minimal (Hartmann & Rafiee Rad, 2012)

Consequence of updating: Effect is *content specific*.

p	$P(p \wedge q)$	$P(p \wedge \neg q)$	•	p'	$P(p' \wedge q')$	$P(p' \wedge \neg q')$
$\neg p$	$P(\neg p \wedge q)$	$P(\neg p \wedge \neg q)$		$\neg p'$	$P(\neg p' \wedge q')$	$P(\neg p' \wedge \neg q')$

BAYESIAN UPDATING

Reduced Inferences (Week 1)

Full Inferences (Week 2)

If a girl had sexual intercourse, then she

Role of conditional in Bayesian models:

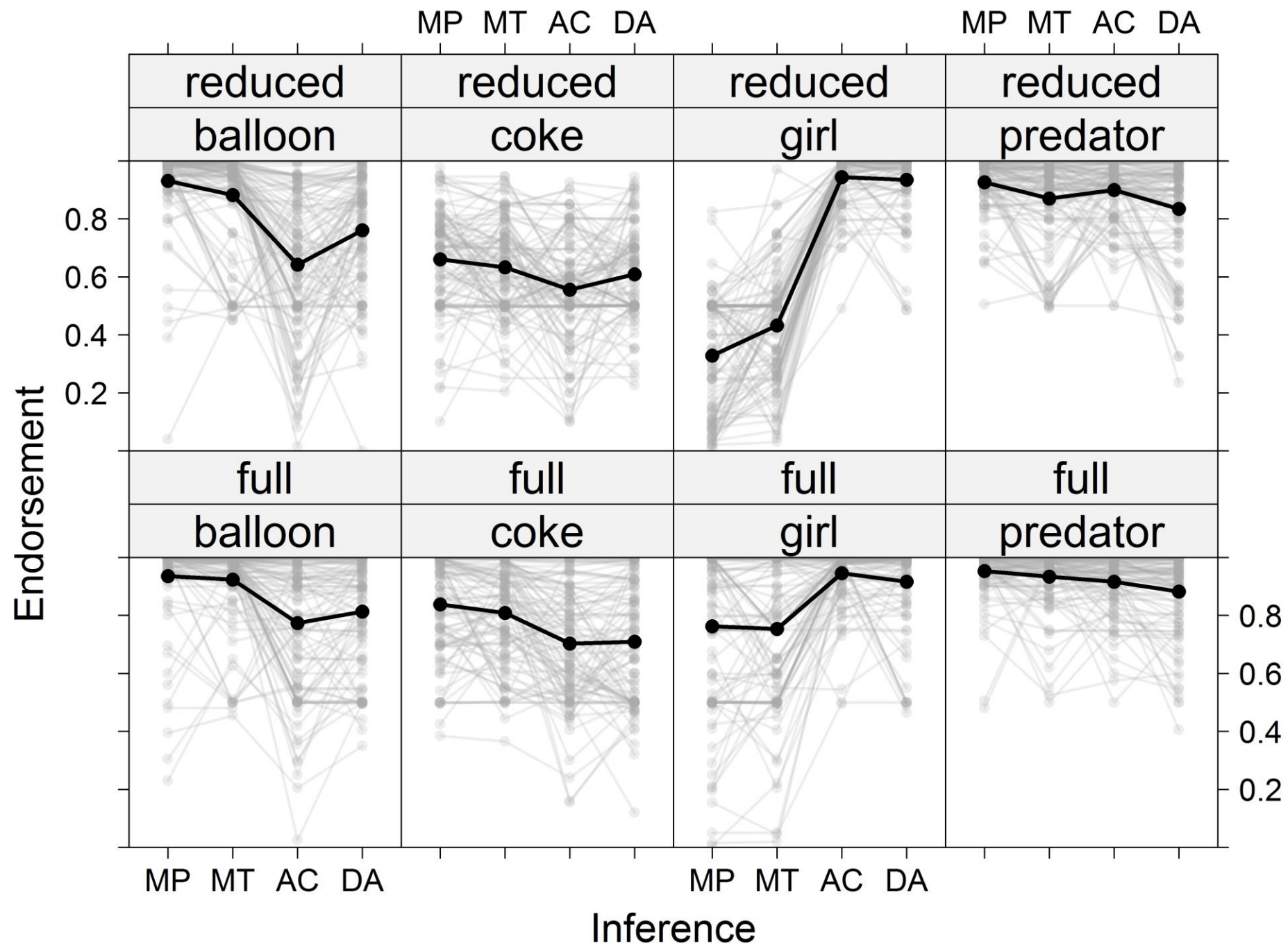
- **PROB:** increases probability of conditional, $P(q | p)$ (Oaksford et al., 2000): $e' < e$
- **EX-PROB:** increases probability of conditional $P_{MP}(q | p) > P_{other}(q | p)$ (Oaksford & Chater, 2007)
- **KL:** increases $P(q | p)$ & Kullback-Leibler distance between $F_{p,q}$ and $F_{p,q}'$ is minimal (Hartmann & Rafiee Rad, 2012)

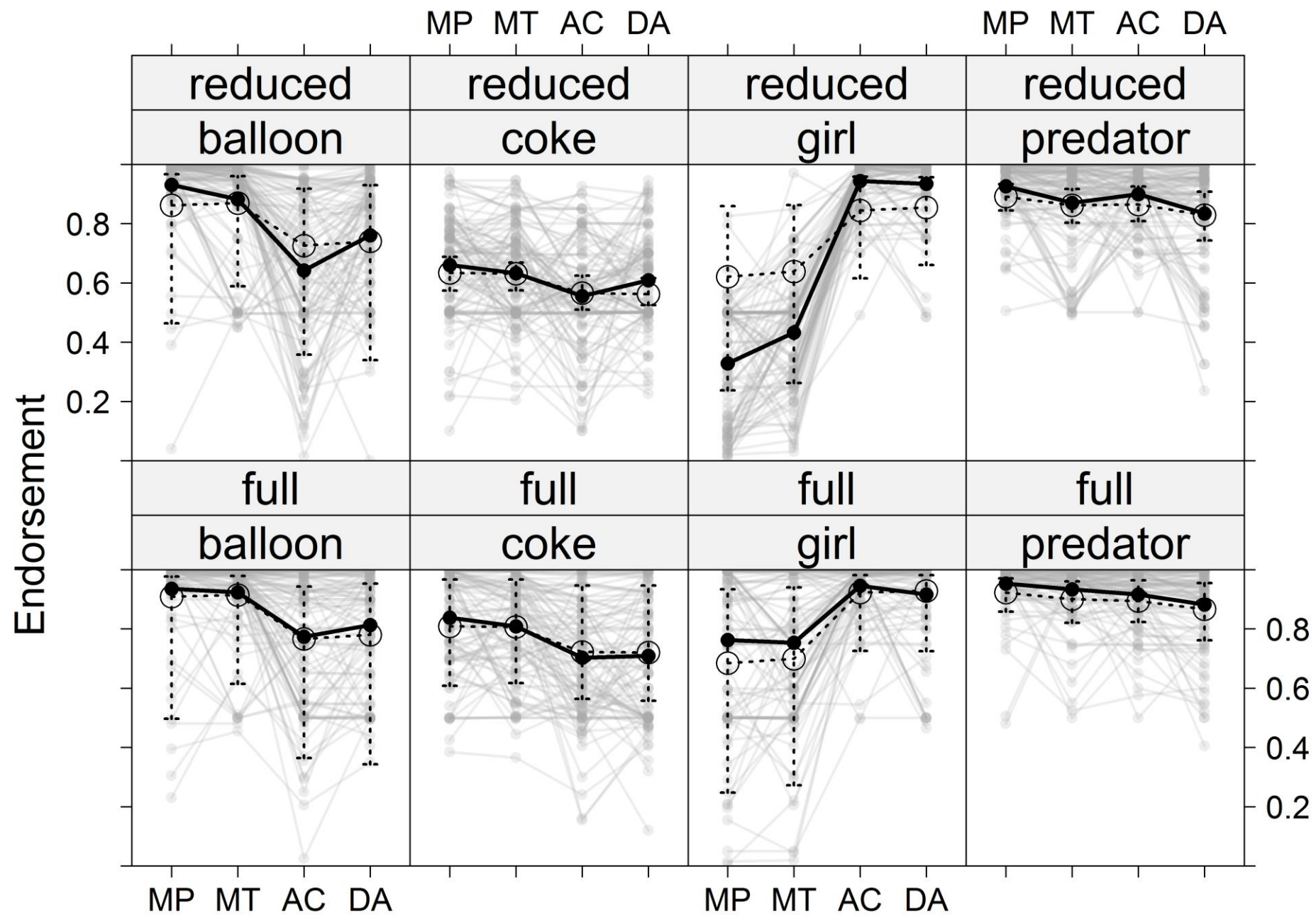
Consequence of updating: Effect is *content specific*.

p	$P(p \wedge q)$	$P(p \wedge \neg q)$
$\neg p$	$P(\neg p \wedge q)$	$P(\neg p \wedge \neg q)$

•

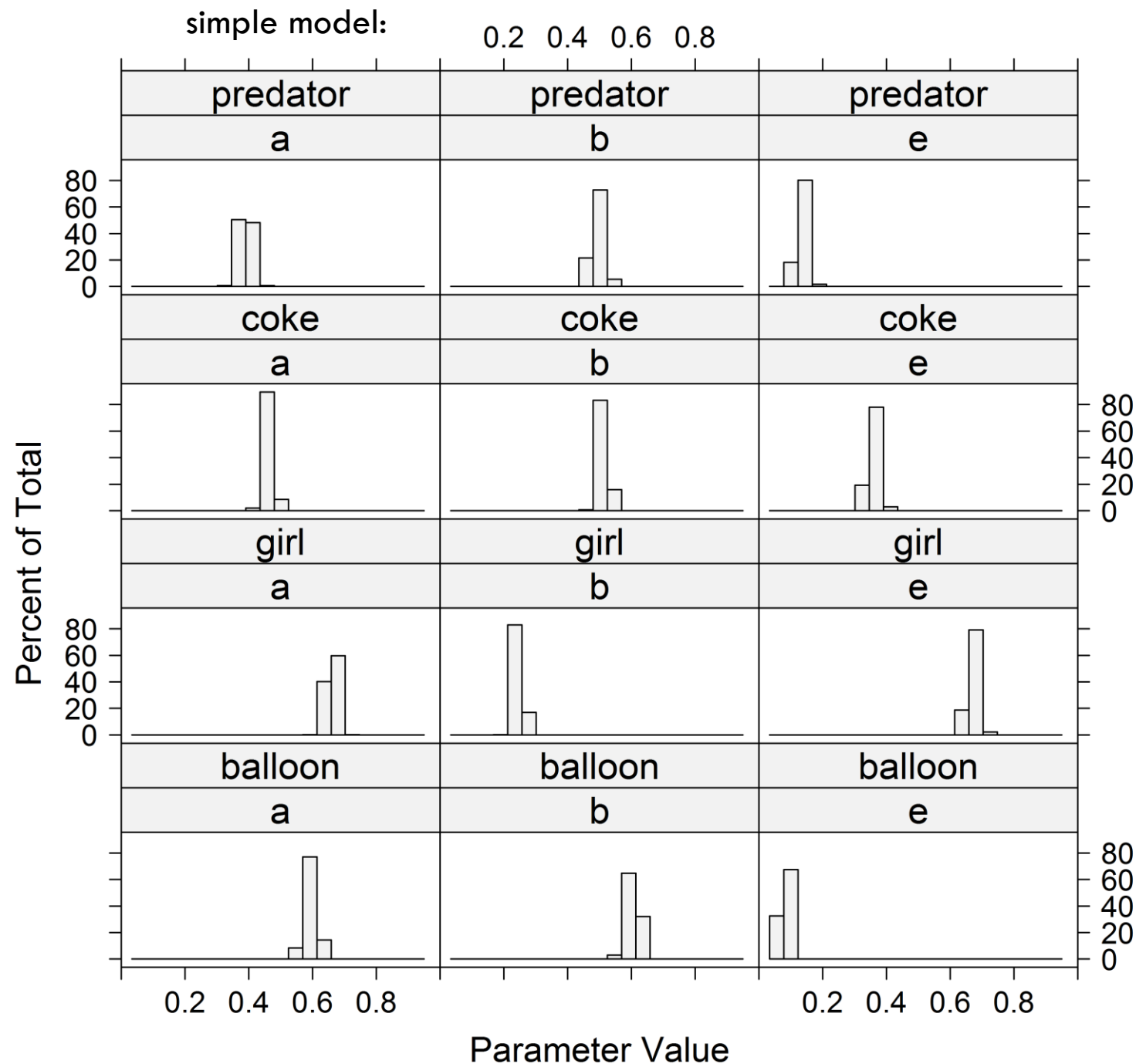
p'	$P(p' \wedge q')$	$P(p' \wedge \neg q')$
$\neg p'$	$P(\neg p' \wedge q')$	$P(\neg p' \wedge \neg q')$





Inference

Black error bars: Range of individual level predictions



Balloon: If a balloon is pricked with a needle then it will pop.

- few disablers, many alternatives

Coke: If a person drinks a lot of coke then the person will gain weight.

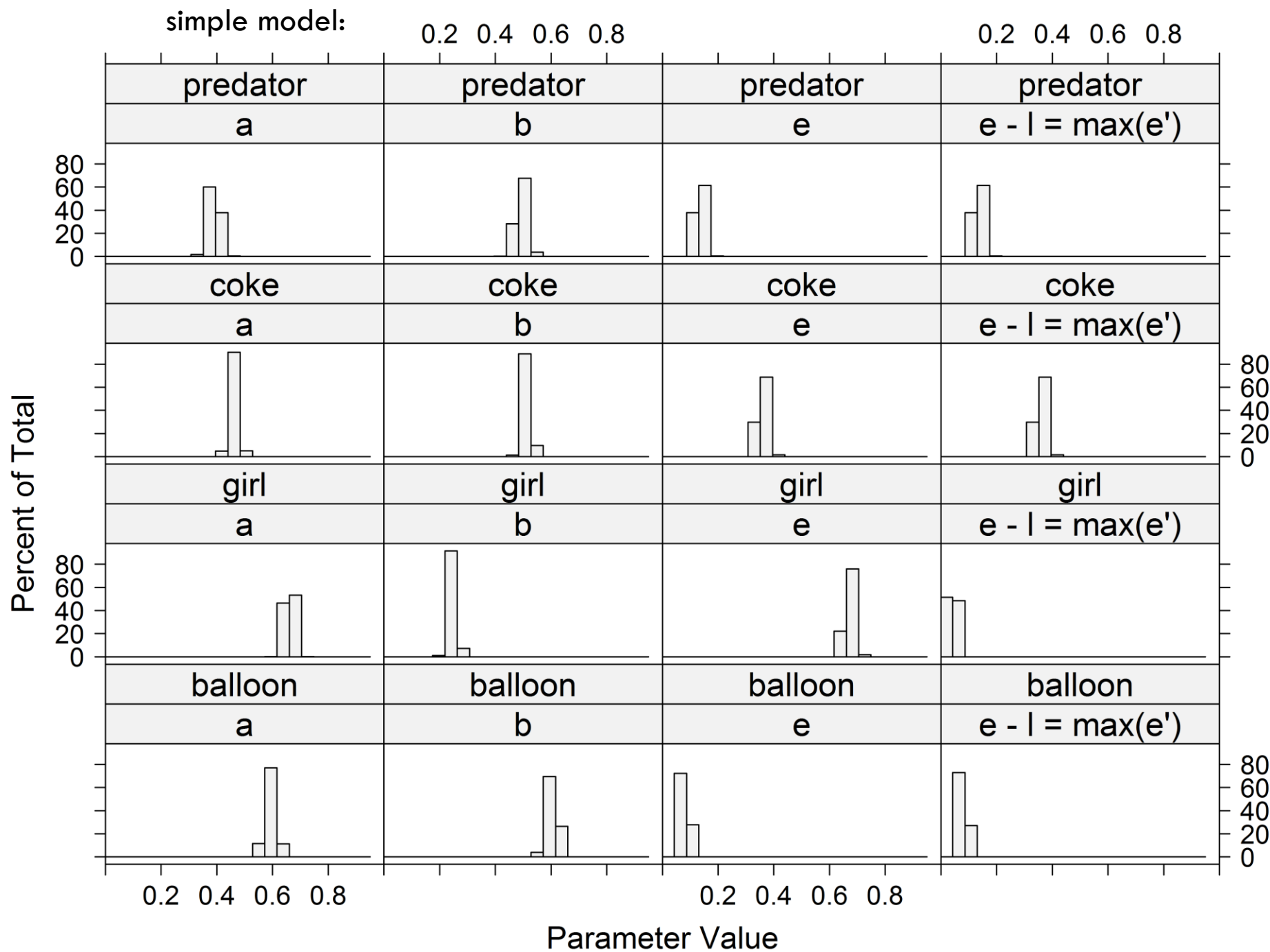
- many disablers, many alternatives

Girl: If a girl has sexual intercourse then she will be pregnant.

- many disablers, few alternatives

Predator: If a predator is hungry then it will search for prey.

- few disablers, few alternatives



Balloon: If a balloon is pricked with a needle then it will pop.

- few disablers, many alternatives

Coke: If a person drinks a lot of coke then the person will gain weight.

- many disablers, many alternatives

Girl: If a girl has sexual intercourse then she will be pregnant.

- many disablers, few alternatives

Predator: If a predator is hungry then it will search for prey.

- few disablers, few alternatives

PROB:

0.2 0.4 0.6 0.8

0.2 0.4 0.6 0.8

100
80
60
40
20
0

predator

predator

predator

predator

predator

a

b

e

$e - l = \max(e')$

e'

coke

coke

coke

coke

coke

a

b

e

$e - l = \max(e')$

e'

girl

girl

girl

girl

girl

a

b

e

$e - l = \max(e')$

e'

balloon

balloon

balloon

balloon

balloon

a

b

e

$e - l = \max(e')$

e'

100
80
60
40
20
0

100
80
60
40
20
0

100
80
60
40
20
0

0.2 0.4 0.6 0.8

0.2 0.4 0.6 0.8

0.2 0.4 0.6 0.8

Parameter Value

Percent of Total

BAYESIAN UPDATING

Reduced Inferences (Week 1)

Full Inferences (Week 2)

If a girl had sexual intercourse, then she

Role of conditional in Bayesian models:

- ~~• *PROB*: increases probability of conditional, $P(q|p)$ (Oaksford et al., 2000): $e' < e$~~
- ~~• *EX-PROB*: increases probability of conditional $PMP(q|p) > Pother(q|p)$ (Oaksford & Chater, 2007)~~
- *KL*: increases $P(q|p)$ & Kullback-Leibler distance between $F_{p,q}$ and $F_{p,q}'$ is minimal (Hartmann & Rafiee Rad, 2012)

Consequence of updating: Effect is content specific.

p	$P(p \wedge q)$	$P(p \wedge \neg q)$
$\neg p$	$P(\neg p \wedge q)$	$P(\neg p \wedge \neg q)$

•

p'	$P(p' \wedge q')$	$P(p' \wedge \neg q')$
$\neg p'$	$P(\neg p' \wedge q')$	$P(\neg p' \wedge \neg q')$

Kullback-Leibler (KL) Modell

Hartmann & Rafiee Rad (2012)

Singmann, Klauer, & Beller (2016, Exp. 1 & 3)

Parameterization of $F_{p,q}$: For $F_{p,q}'$:

- $h = P(q)$
- $\alpha = P(q|p)$
- $\beta = P(q|\neg p)$
- $\alpha' > \alpha$
- Kullback-Leibler divergence between $F_{p,q}$ and $F_{p,q}'$ minimal.

$$E_{\text{red},ijk} \sim \text{Beta}(\alpha_{\text{red},ijk}, \beta_{\text{red},ijk})$$

$$E_{\text{full},ijk} \sim \text{Beta}(\alpha_{\text{full},ijk}, \beta_{\text{full},ijk})$$

$$F_{p,q,jk} \sim \text{Dirichlet}(\gamma_j \times \psi_j)$$

$$\delta_{\alpha} \sim \text{MvNormal}(\mathbf{0}, \Sigma_{\alpha})$$

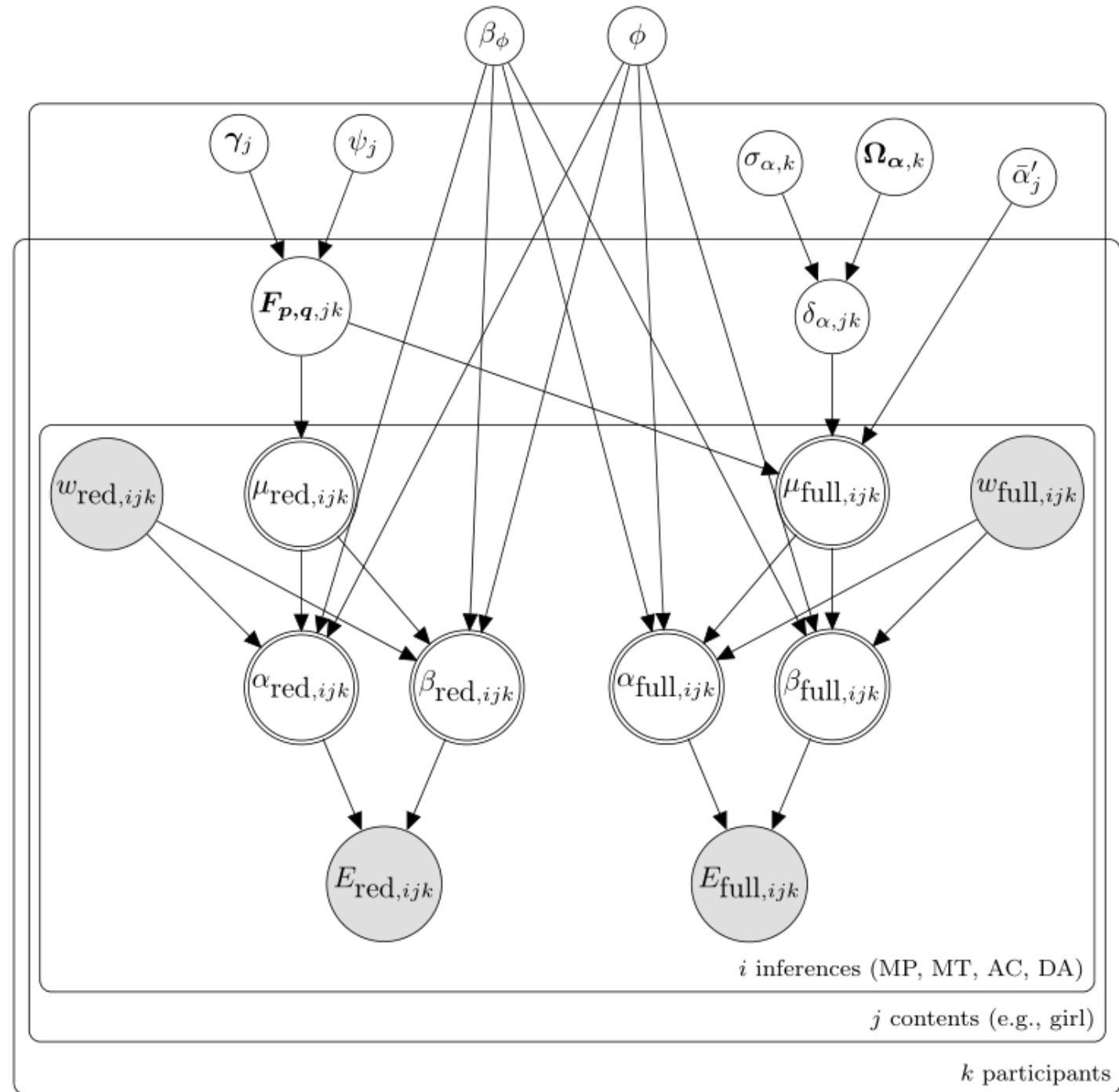
$$\Sigma_{\alpha} = \sigma_{\alpha} \Omega_{\alpha}$$

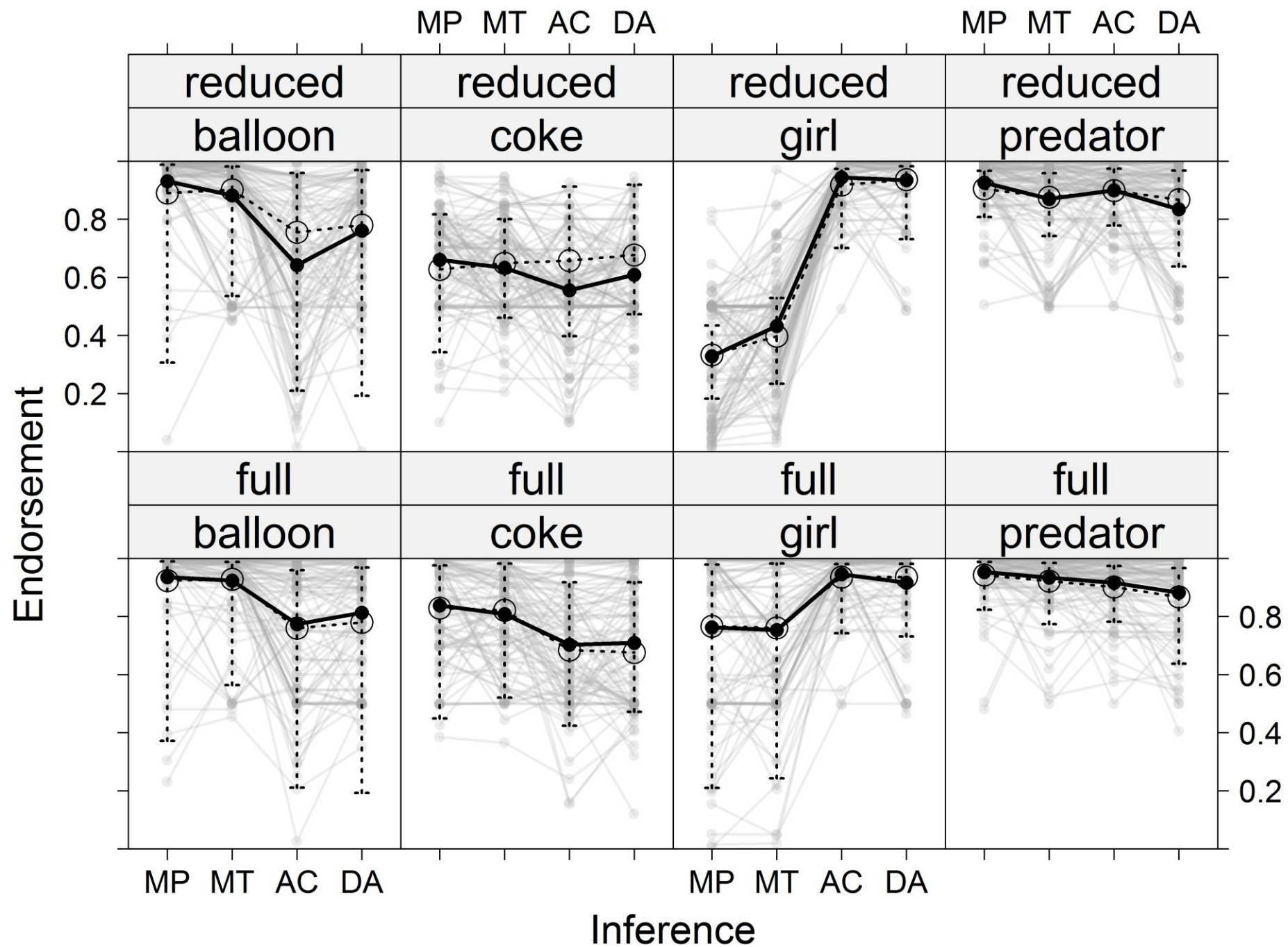
$$\Omega_{\alpha} \sim \text{LKJ}(1)$$

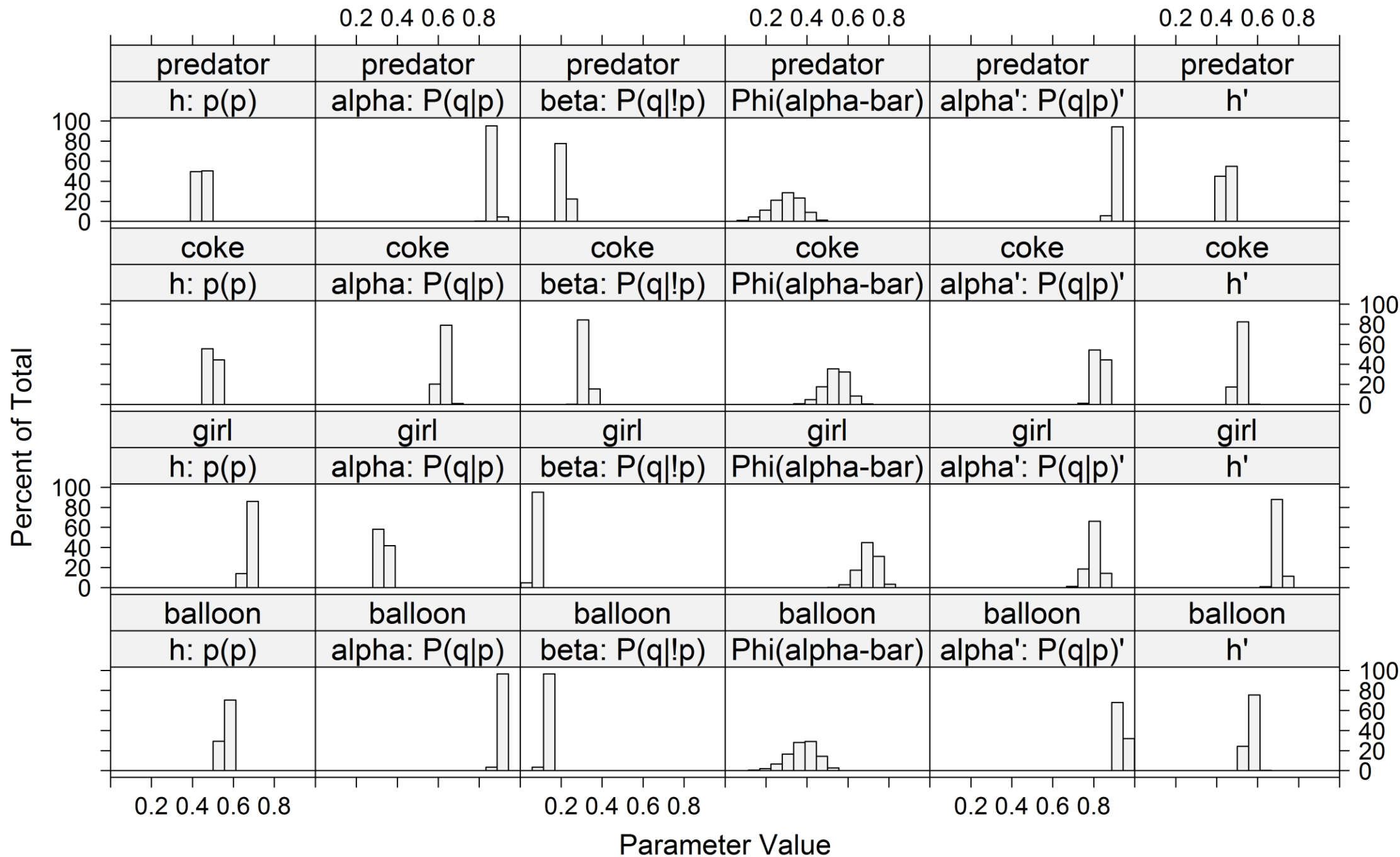
$$\sigma_{\alpha,k} \sim \text{Cauchy}^+(0, 4)$$

$$\bar{\alpha}'_j \sim \text{Normal}(0, 1)$$

$$\alpha'_{ij} = \alpha_{ij} + (1 - \alpha_{ij}) \times \Phi(\bar{\alpha}'_j + \delta_{\alpha,jk})$$



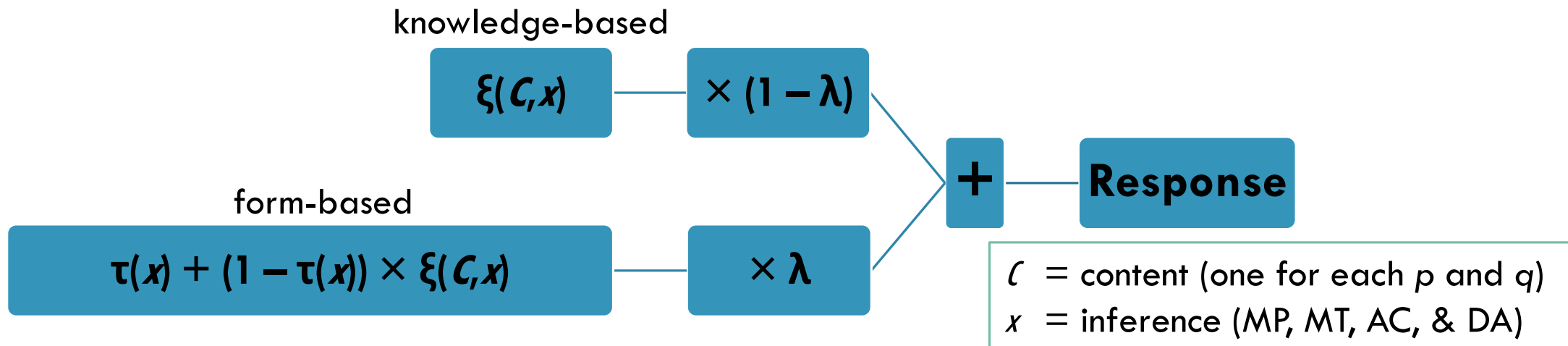




DUAL-SOURCE MODEL (DSM)

Klauer, Beller, & Hütter (2010, Exp. 1)
Singmann, Klauer, & Beller (2016, Exp. 1 & 3)

Par.	Interpretation	Influencing Factors
λ	Relative weight given to form-based versus knowledge-based evidence	E.g., speaker expertise, instructional emphasis on rule
τ	Degree to which an inference is seen as logically warranted	E.g., inference (MP, MT, AC, DA), connective (e.g., “if -then” vs. “or”)
ξ	Knowledge-based response proposal	E.g., contents of the premises/ salience of counterexamples



$$E_{\text{red},ijk} \sim \text{Beta}(\alpha_{\text{red},ijk}, \beta_{\text{red},ijk})$$

$$E_{\text{full},ijk} \sim \text{Beta}(\alpha_{\text{full},ijk}, \beta_{\text{full},ijk})$$

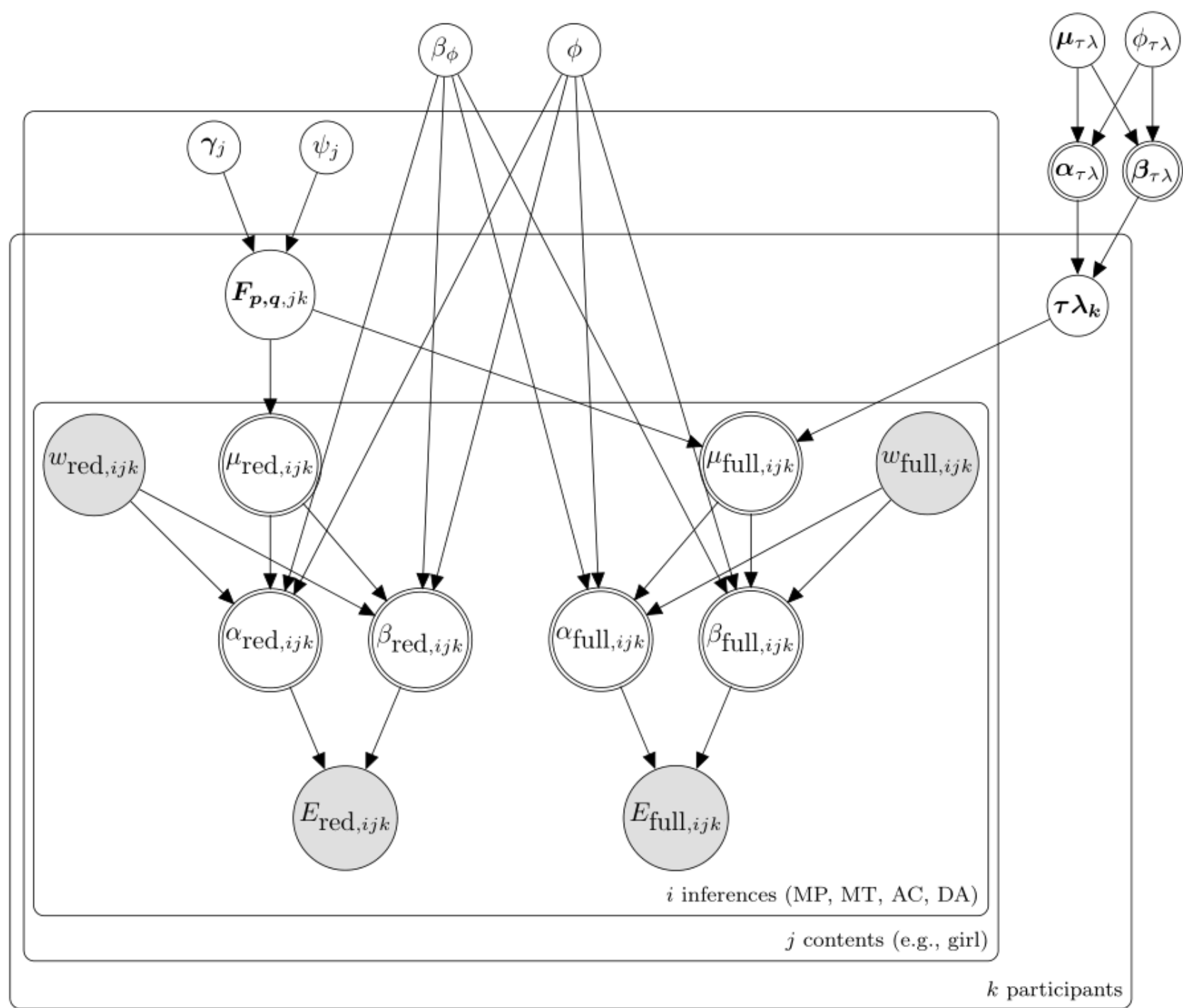
$$\tau \lambda_k \sim \text{Beta}(\alpha_{\tau\lambda}, \beta_{\tau\lambda})$$

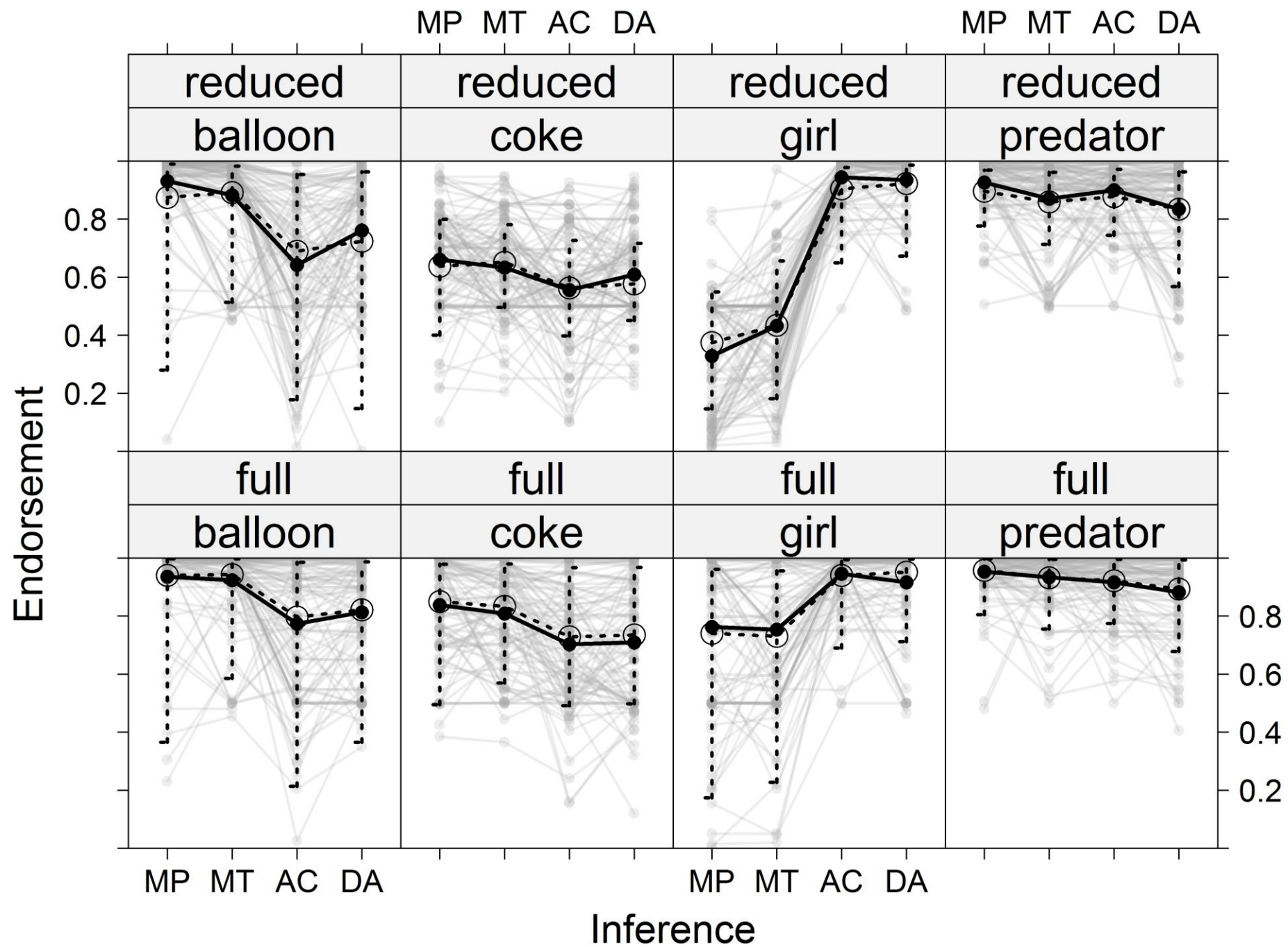
$$\mu_{\tau\lambda} \sim \text{Uniform}(0, 1)$$

$$\phi_{\tau\lambda} \sim \text{Cauchy}^+(0, 5)$$

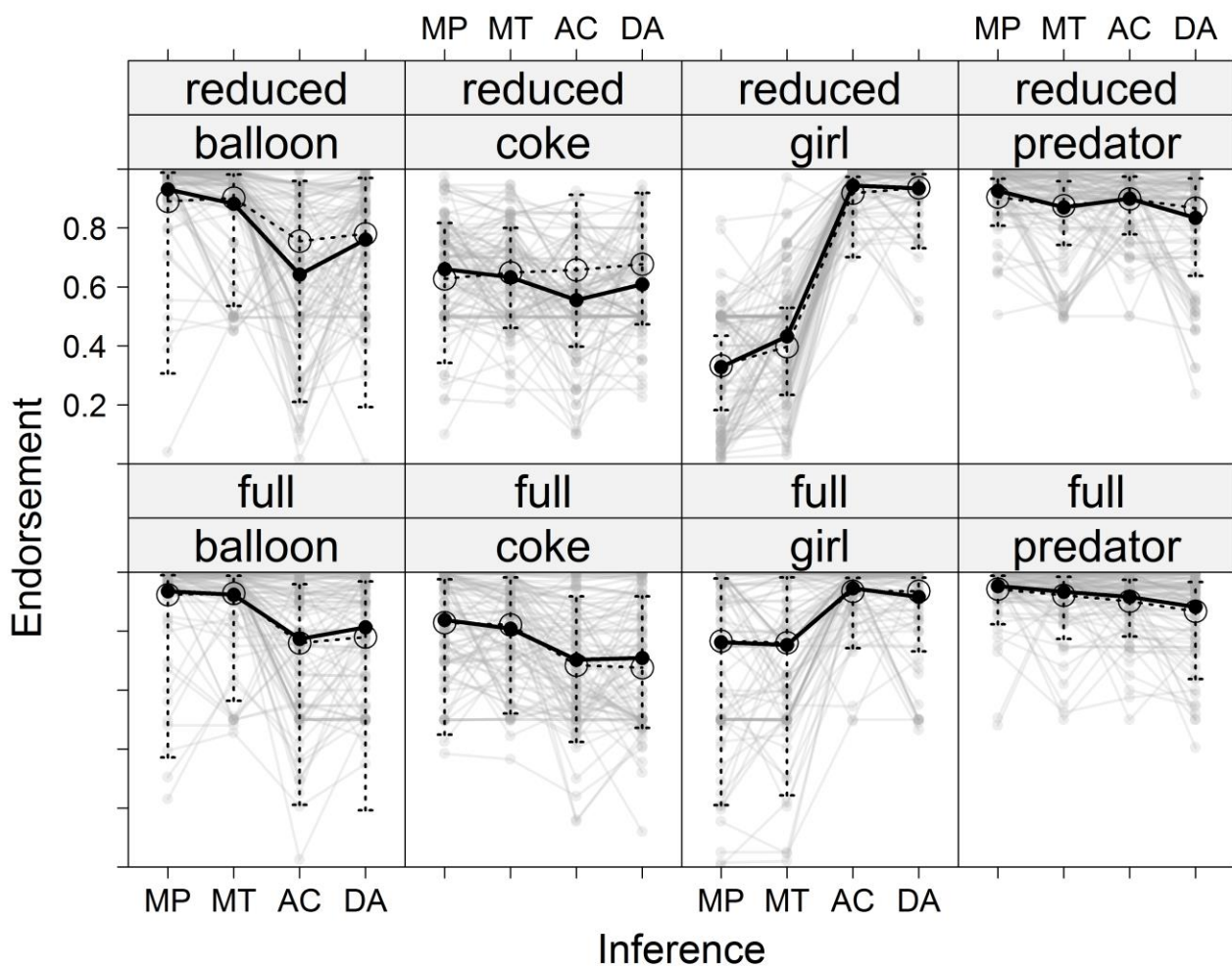
$$\lambda_k = \max(\tau \lambda_k)$$

$$\tau_k = \frac{\tau \lambda_k}{\lambda_k}$$

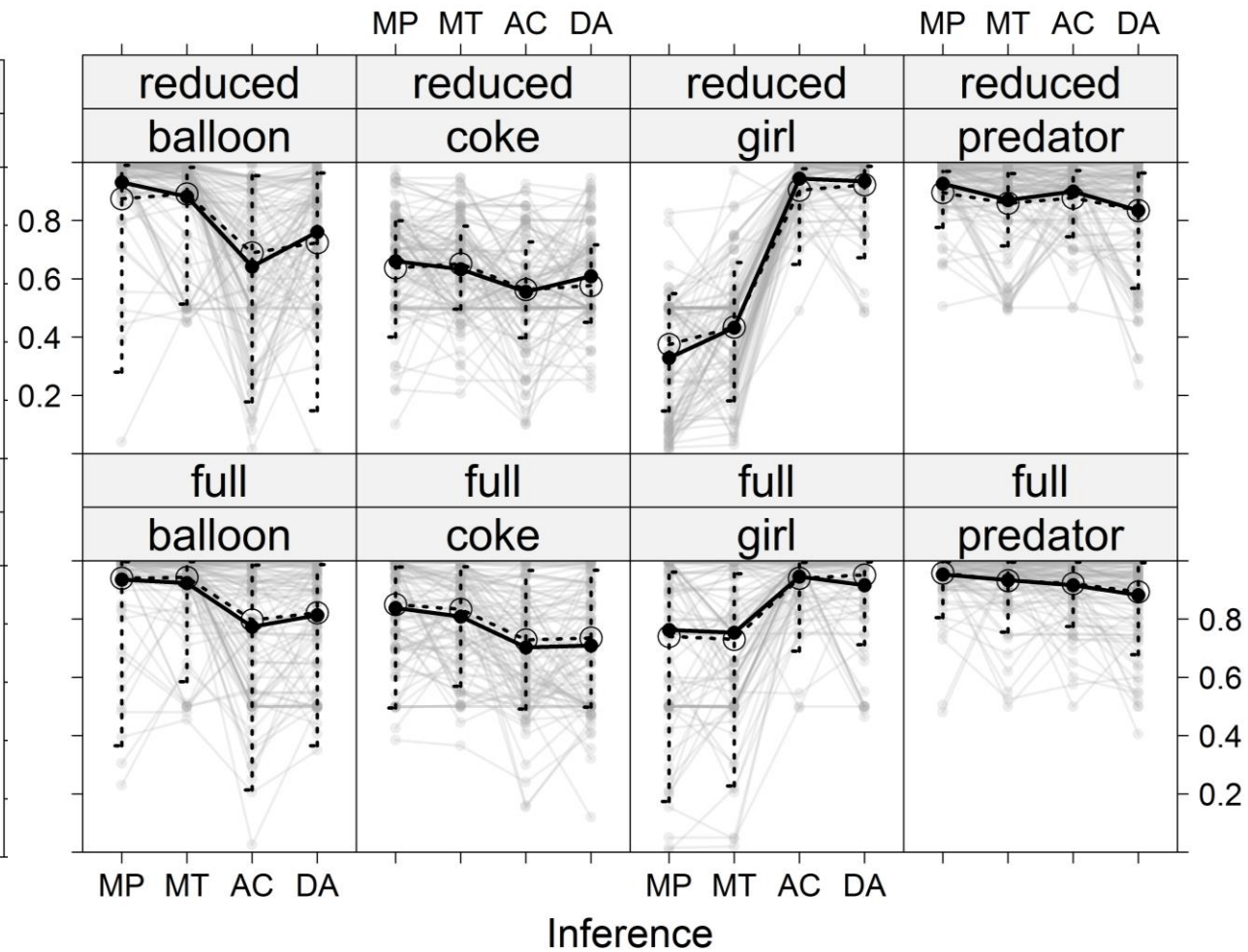




KL Model:



DSM:



SUMMARY: HIERARCHICAL BAYESIAN IMPLEMENTATION OF BAYESIAN MODELS OF REASONING

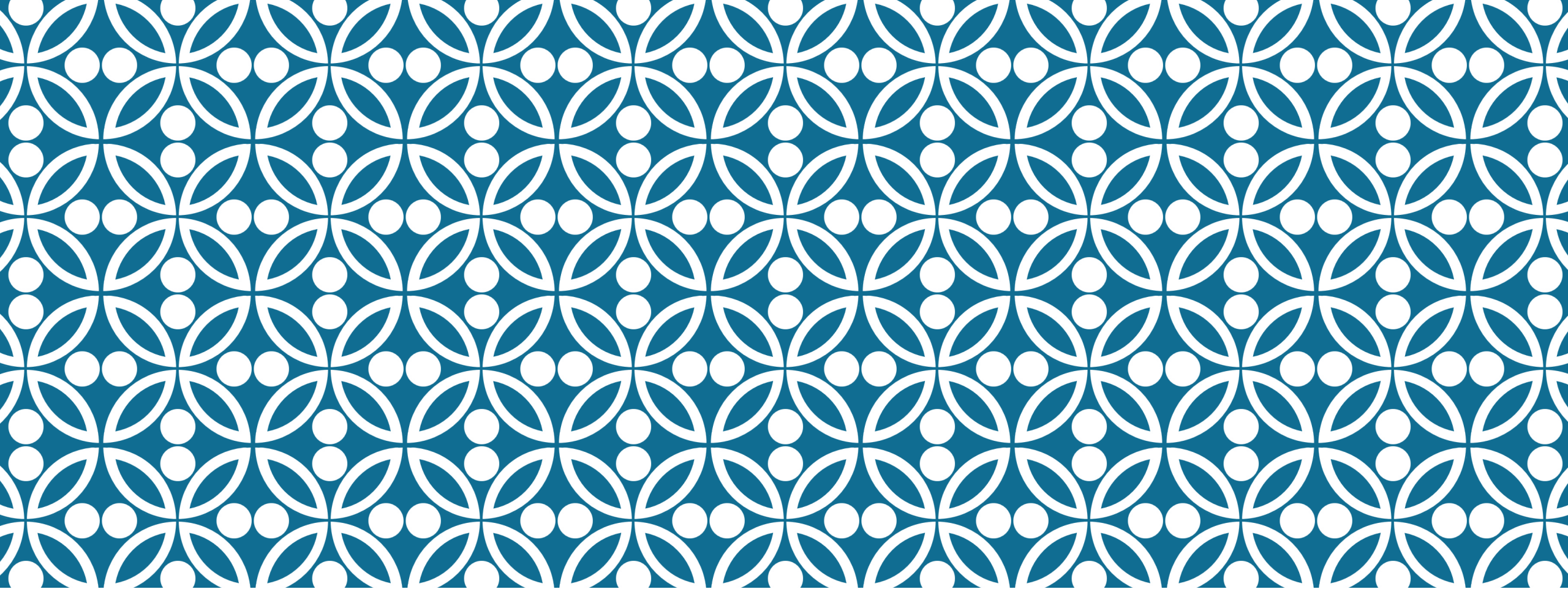
Bayesian statistics offer:

- Principled approach to model individual differences
- Allows investigation of individual level and group-level parameters
- Provides additional information (e.g., precision of probability distribution estimates, correlation among individual parameters)

For inferences without conditional (i.e., purely knowledge) a simple Bayesian model provides good account.

Learning a conditional can be modeled with:

- Bayesian model that assumes unconstrained updating of $P(q|p)$ and KL minimization (Hartmann & Rafiee Rad, 2012).
- Dual-Source Model (Klauer et al., 2010; Singmann et al., 2016), which assumes individuals combine background knowledge with the subjective probability with which they see a specific inference as logically warranted.



THAT WAS ALL

$F_{p,q}$: If a balloon is pricked with a needle then it will pop.		
ψ_j : 15 [27]	q	$\neg q$
p	.36	.06
$\neg p$.16	.42

$F_{p,q}$: If a person drinks a lot of coke then the person will gain weight.		
ψ_j : 58 [250]	q	$\neg q$
p	.29	.17
$\neg p$.23	.31

$F_{p,q}$: If a girl has sexual intercourse then she will be pregnant.		
ψ_j : 33 [21]	q	$\neg q$
p	.24 [.35]	.41 [.21]
$\neg p$.03 [.07]	.31 [.37]

$F_{p,q}$: If a predator is hungry then it will search for prey.		
ψ_j : 46 [130]	q	$\neg q$
p	.51	.06
$\neg p$.07	.36

$F_{p,q}$: If a balloon is pricked with a needle then it will pop.		
ψ_j : 15 [27]	q	$\neg q$
p	.36	.06
$\neg p$.16	.42

Precision of group-level parameter for $F_{p,q}$ (ψ_j), initial model:

10.5 [8.2, 13.2]

19.3 [13.8, 27.3]

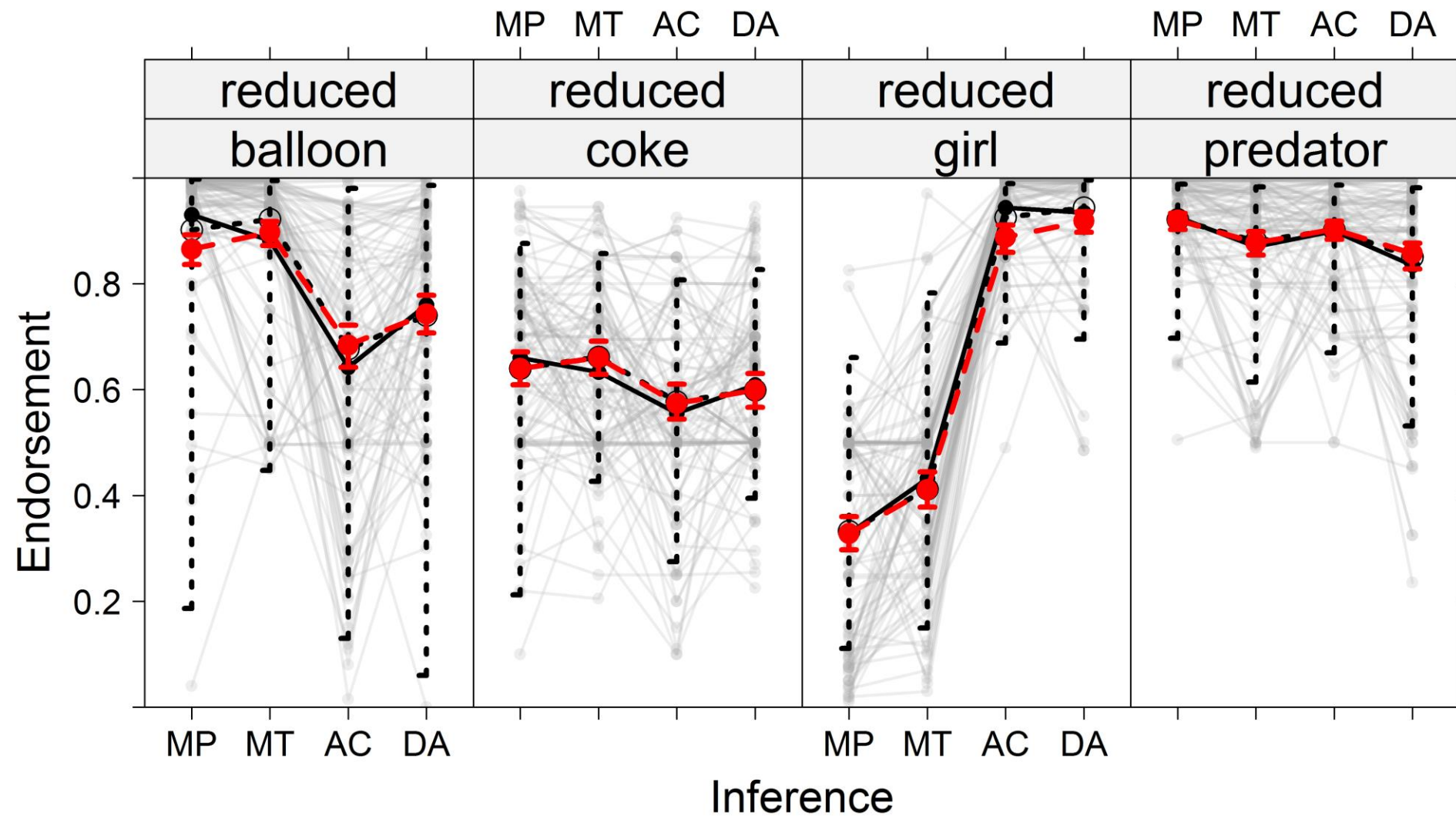
$F_{p,q}$: If a girl has sexual intercourse then she will be pregnant.		
ψ_j : 33 [21]	q	$\neg q$
p	.24 [.35]	.41 [.21]
$\neg p$.03 [.07]	.31 [.37]

$F_{p,q}$: If a person drinks a lot of coke then the person will gain weight.		
ψ_j : 58 [250]	q	$\neg q$
p	.29	.17
$\neg p$.23	.31

27.1 [20.3, 37.0]

27.3 [20.1, 36.9]

$F_{p,q}$: If a predator is hungry then it will search for prey.		
ψ_j : 46 [130]	q	$\neg q$
p	.51	.06
$\neg p$.07	.36



Black error bars: Range of individual level predictions from simple model

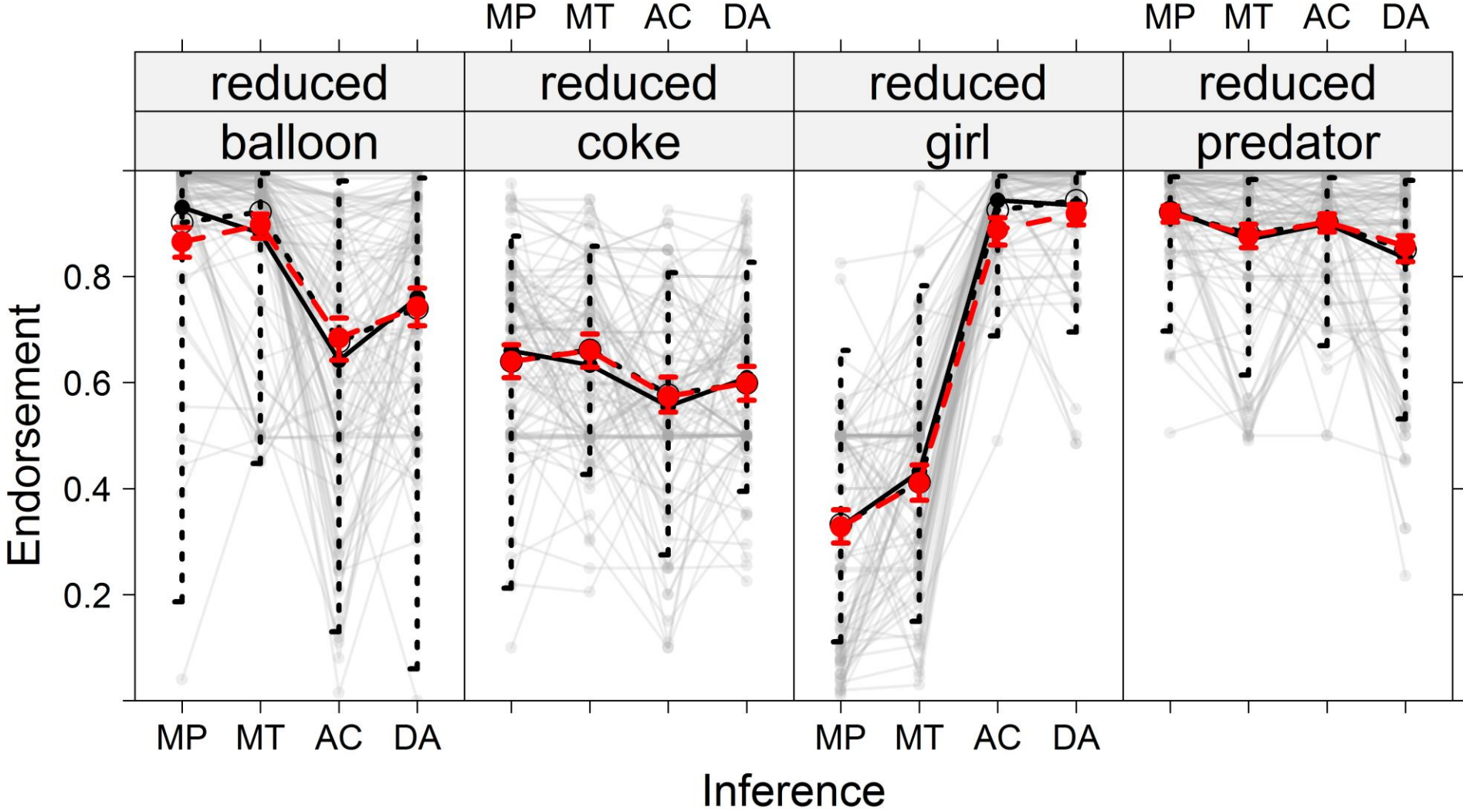
Precision of group-level
parameter for $F_{p,q}(\psi_j)$:

10.5 [8.2, 13.2]

27.1 [20.3, 37.0]

19.3 [13.8, 27.3]

27.3 [20.1, 36.9]



Black error bars: Range of individual level predictions from simple model