Computational Evidence for the Validity of the Balloon Risk Aversion Task

(BRAT)

Sang Min Jung (2021.06.09)

Abstract

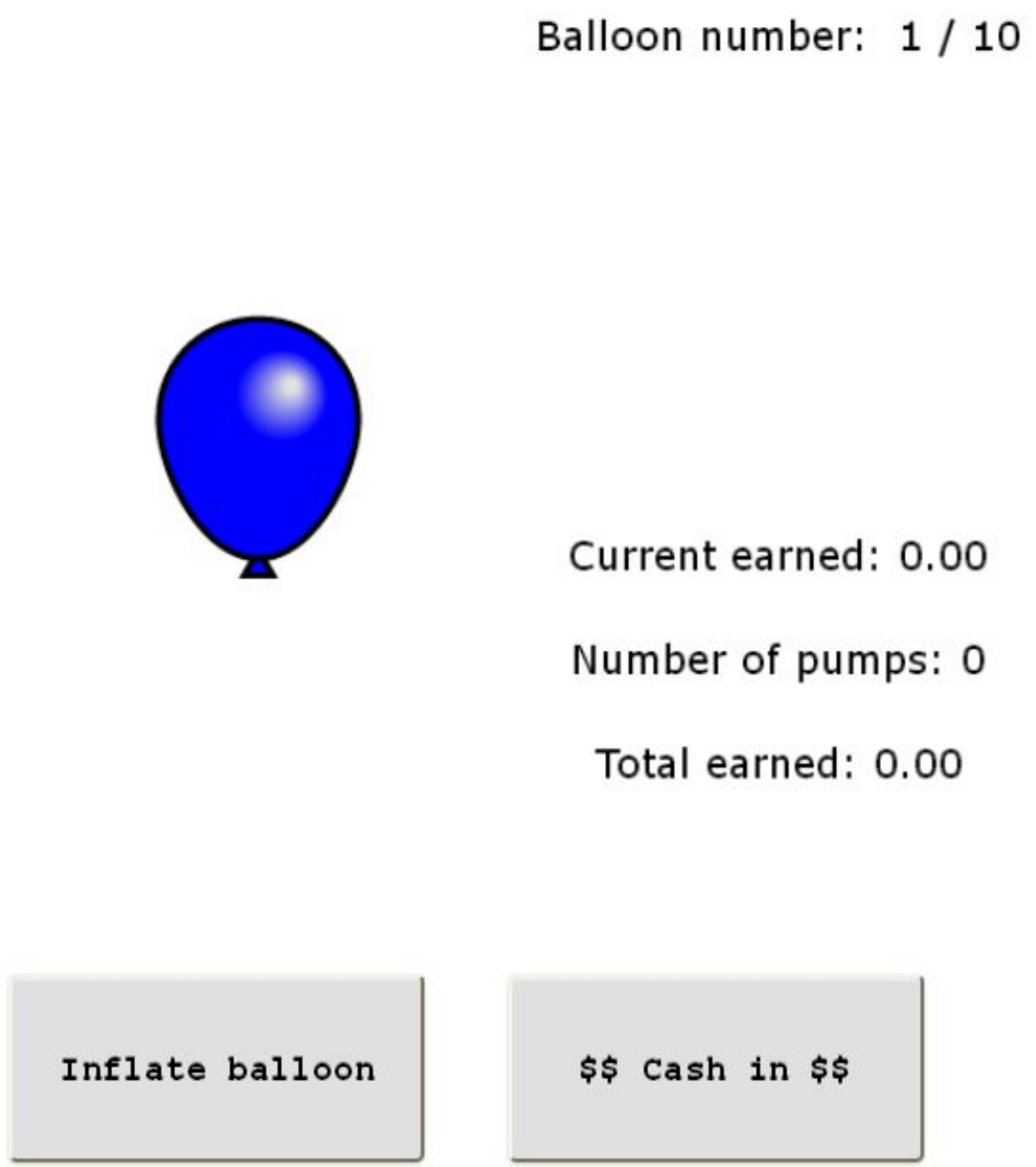
By inverting the design of the BART task, Balloon Risk Aversion Task attempts to isolate the avoidance motivation and explore its uniqueness compared to risk taking (approach motivation). Through this project, we explore the computational evidence for whether the change in the task's design has succeeded in changing the cognitive processes of the subject. Two criteria are used: 1) Do the subjects measure risk based on how much risk they avoided or took? 2) Do the subjects view the situation as loss-only context? Through fitting of four different model designs using hierarchal Bayesian inference and MLE (Maximum Likelihood Estimation), we were able to find computational evidence for change in subjects' method of calculating risk but no evidence that they view loss from the task. While the best model showed big difference in LOOIC, AIC, and BIC, it showed poor performance in parameter recovery. Improvements in model design concerning how subjects learn during BRAT task seems necessary.

Task & Motivation

Balloon Analog Risk Task (BART)

- Offered chance to earn points by pumping a balloon
- Each pump has the chance to over-inflate the balloon and pop it
- Can choose to stop pumping and cash in

(Lejuez et al., 2002)



Motivation for a new behavioral task

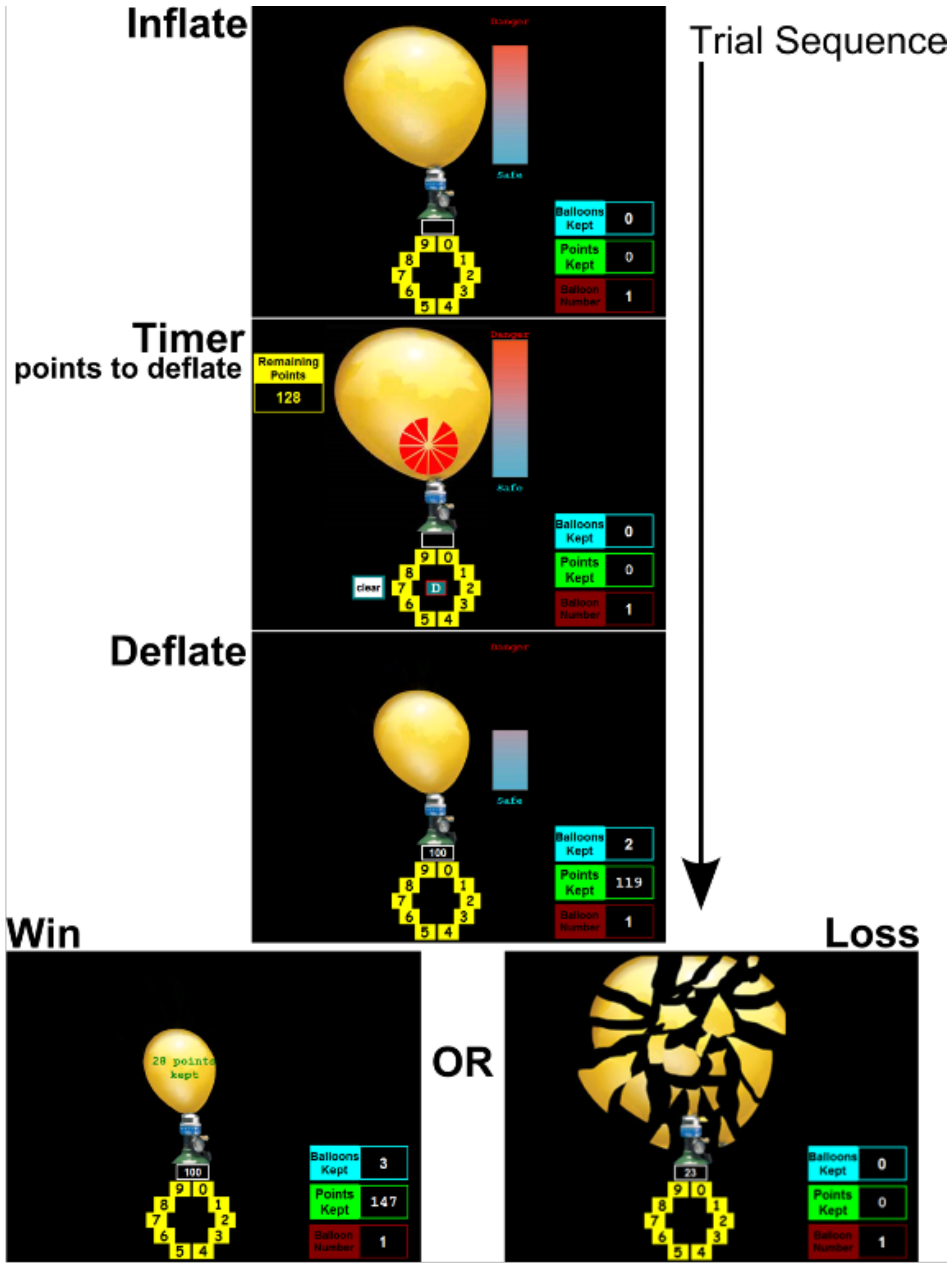
"Admittedly, most if not all, behavioral tasks aimed at understanding risk-taking or risk-aversion can have both approach and avoidance motivation." (Crowley et al., under review)

Risk Taking vs Risk Aversion

Balloon Risk Aversion Task (BRAT)

- A balloon at full capacity, certain to explode without any action, is presented.
- Can choose to deflate the balloon to make it “safer”
- Will either explode or be cashed in for the remaining value of the balloon

(Crowley et al., under review)



What's the difference?

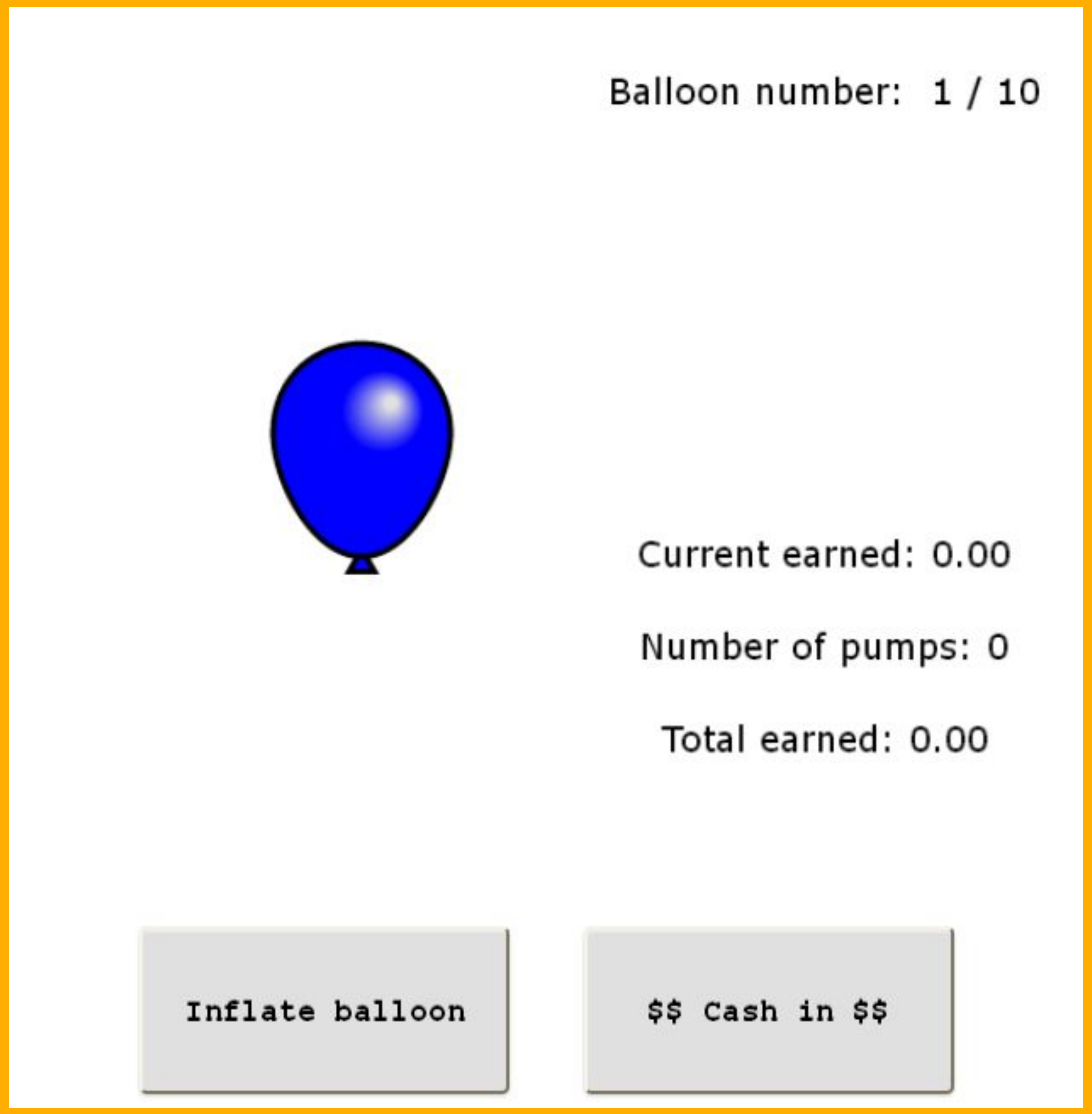
Bias participants toward avoidance rather approach

Create a loss-only context

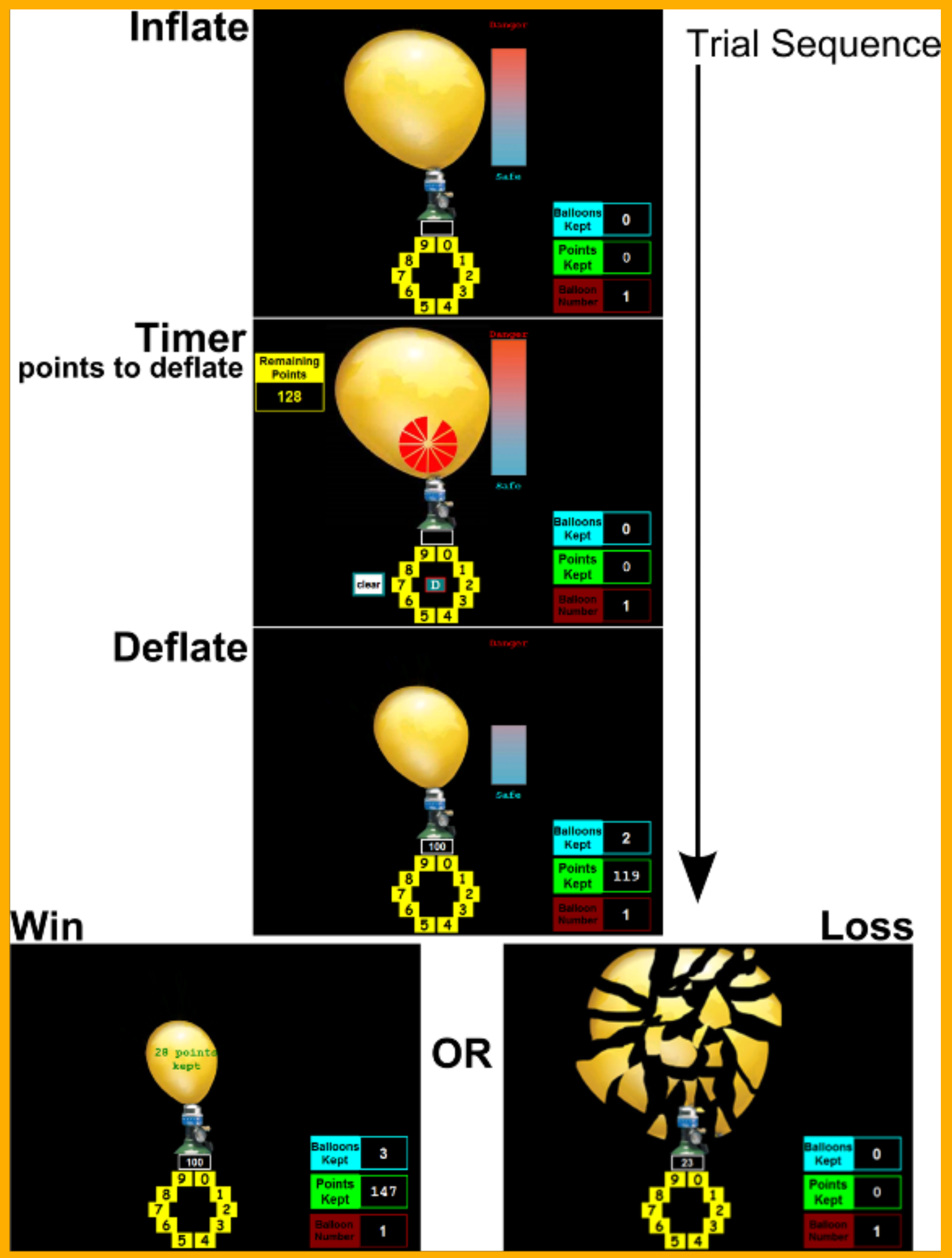
Capture the individual variability in avoidance (risk aversion)

Goal

Come up with a Computational Model for BRAT



BART



BRAT

Method

Model Design

Expected Utility: Risk Taking vs Risk Aversion

$$U_{kl} = \sum x \times P(x)$$

$P(x)$: When calculating a probability of an event, is the participant basing their calculation on the risk they took or the risk they evaded?

x : When calculating the value of an event, is the participant gain oriented or loss oriented?

Model Design for the BRAT task

4 Parameter Model (BART)

$$p_k^{burst} = 1 - \frac{\phi + \eta \sum n^{success}}{1 + \eta \sum n^{pumps}}$$

Cashed in: $(I - l)^{\gamma}$
Burst: 0

$$U_{kl} = (1 - p_k^{burst})^{(I-l)}(I - l)^{\gamma}$$

(Park et al., 2021)

Model Design for the BRAT task

1. Calculates risk based on how much risk is avoided rather than taken

$$r_k^{deflate} = \frac{\phi + \eta \sum n^{failure}}{1 + \eta \sum n^{pumps}}$$

Cashed in: $(I - l)^{\gamma}$
Burst: 0

$$U_{kl} = (1 - (r_k^{deflate})^{l})(I - l)^{\gamma}$$

p_k^{burst} : the probability that the balloon will burst with a pump

$r_k^{deflate}$: the rate in which the burst of probability reduces with each deflation

Model Design for the BRAT task

1. Calculates risk based on how much risk is avoided rather than taken

Model Design for the BRAT task

2. Loss-only context

$$r_k^{deflate} = \frac{\phi + \eta \sum n^{failure}}{1 + \eta \sum n^{pumps}}$$

Cashed in: $-\, l^{\gamma}$

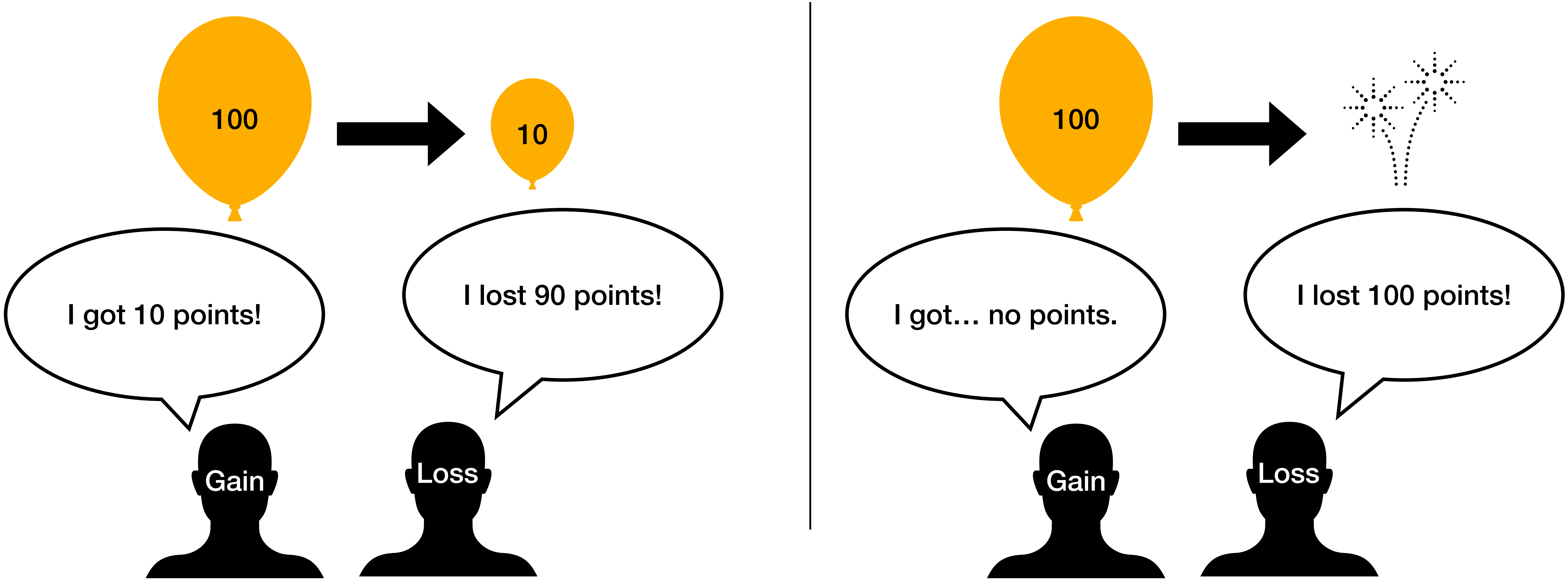
Burst: $-\, I^{\gamma}$

$$U_{kl} = -\,(1 - (r_k^{deflate})^l)(l)^{\gamma} - (r_k^{deflate})^l (I)^{\gamma}$$

(Kahneman et al. 1979)

Model Design for the BRAT task

2. Loss-only context

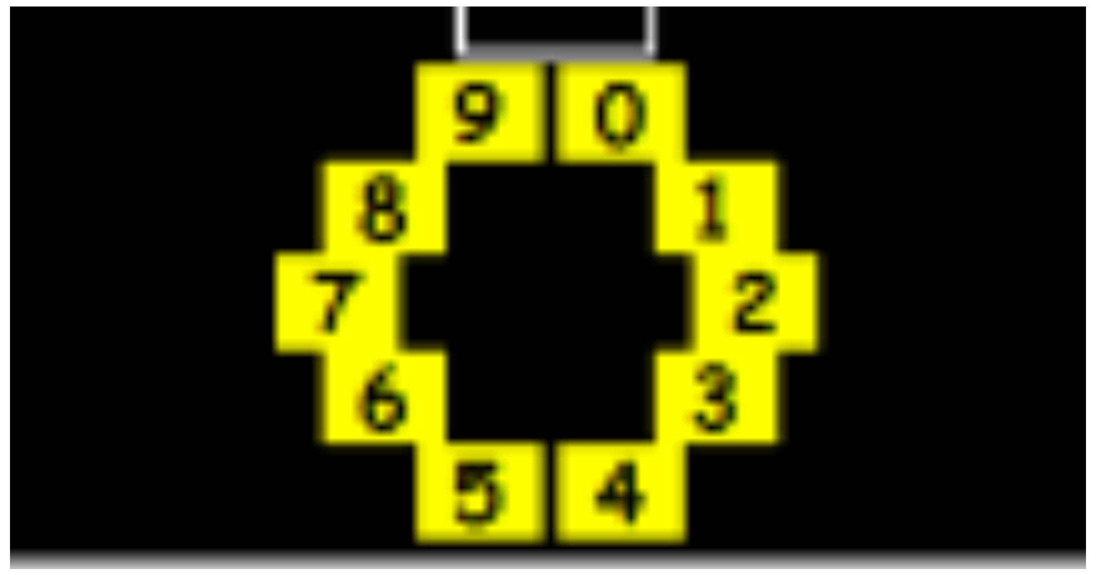


Model Design for the BRAT task

Automatic Design

$$v_k = argmax(U_{kl})$$

$$p_{kl}^{pump} = \frac{1}{1 + e^{\tau(l - v_k)}}$$



$$P(deflation[k] = l) = \frac{exp(\tau \times U_{kl})}{\sum_{j=1}^{I} exp(\tau \times U_{kj})}$$

p_{kl}^{pump} : probability that the agent will pump for the lth time for trial k

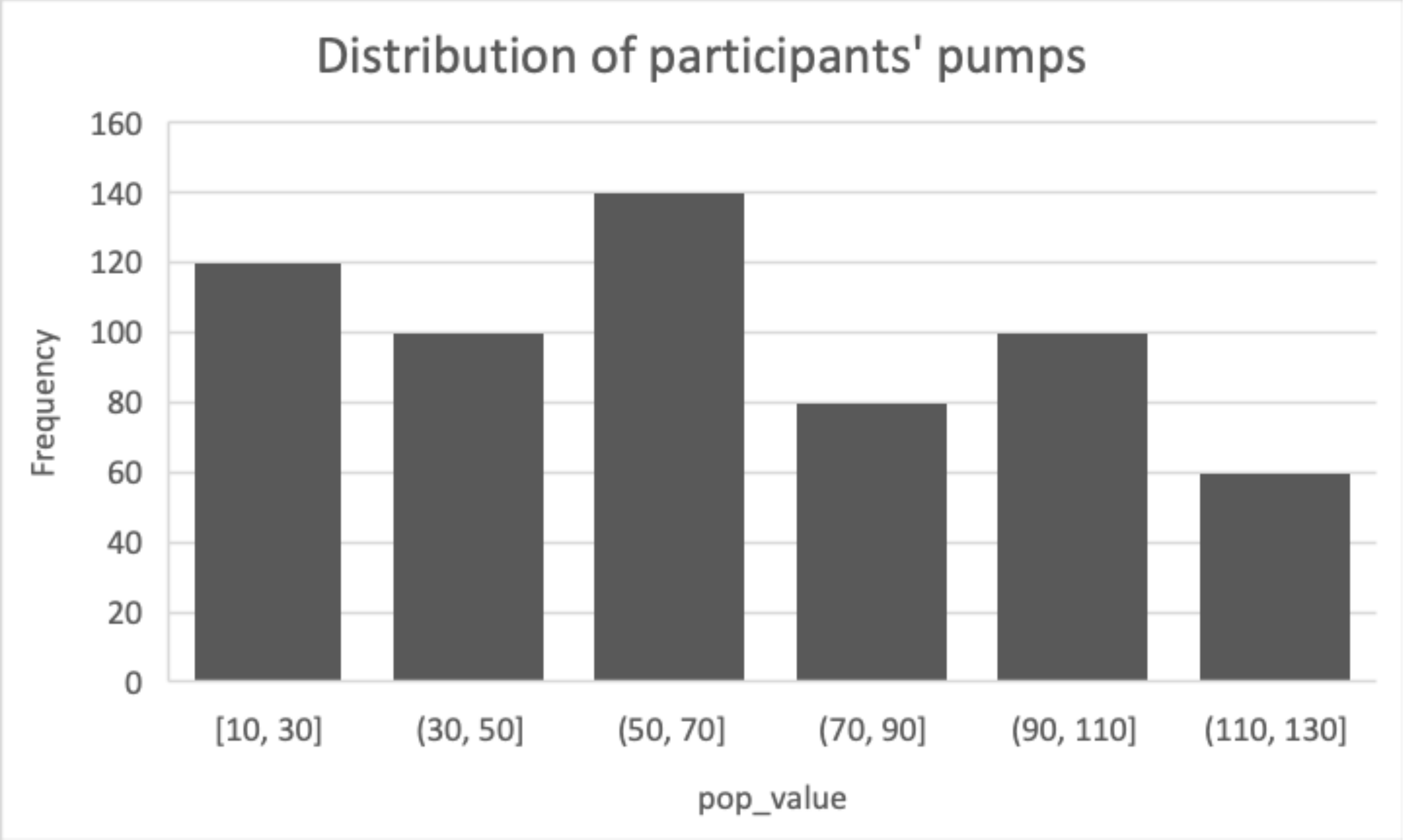
$P(deflation[k] = l)$: Probability that the participant will deflate l times on trial k

Model Design for the BRAT task

	Learns how much risk is taken with each point	Learns how much risk is avoid with each point
Gain-only Context	Model 1	Model 2
Loss-only Context	Model 3	Model 4

Data Statistics

- 30 balloons per participant, 20 participants
- Initial value of the balloon (I) : 128
- Explosion points sampled from normal distribution with a mean of 64



Mean	66.818
SD	24.417

Win	313
Pop	287

Result

Model Fitting

Hierarchal Bayesian Model

- All parameters had group-level parameters. (μ, σ)
- Rstan is used.
- All models were fitted with the following set-up.

  Iter = 3000, warmup = 1000, chain = 4, seed = 1000

  All other settings were set to Stan's default setting.

Result for Bayesian Inference

Parameter Estimation

Each cell shows the posterior mean of its mu, the group-level parameter & Rhat

Model	Model 1	Model 2	Model 3	Model 4
Phi	0.52 / 1	0.98 / 1	0.46 / 1	0.50 / 1
Eta	1.26 / 1	0.98 / 1	1.40 / 1	1.71 / 1
Gamma	0.27 / 1	0.02 / 1	0.1 / 1	0.02 / 1
Tau	0.21 / 1	11.07 / 1	0.77 / 1	0.66 / 1

Result for Bayesian Inference

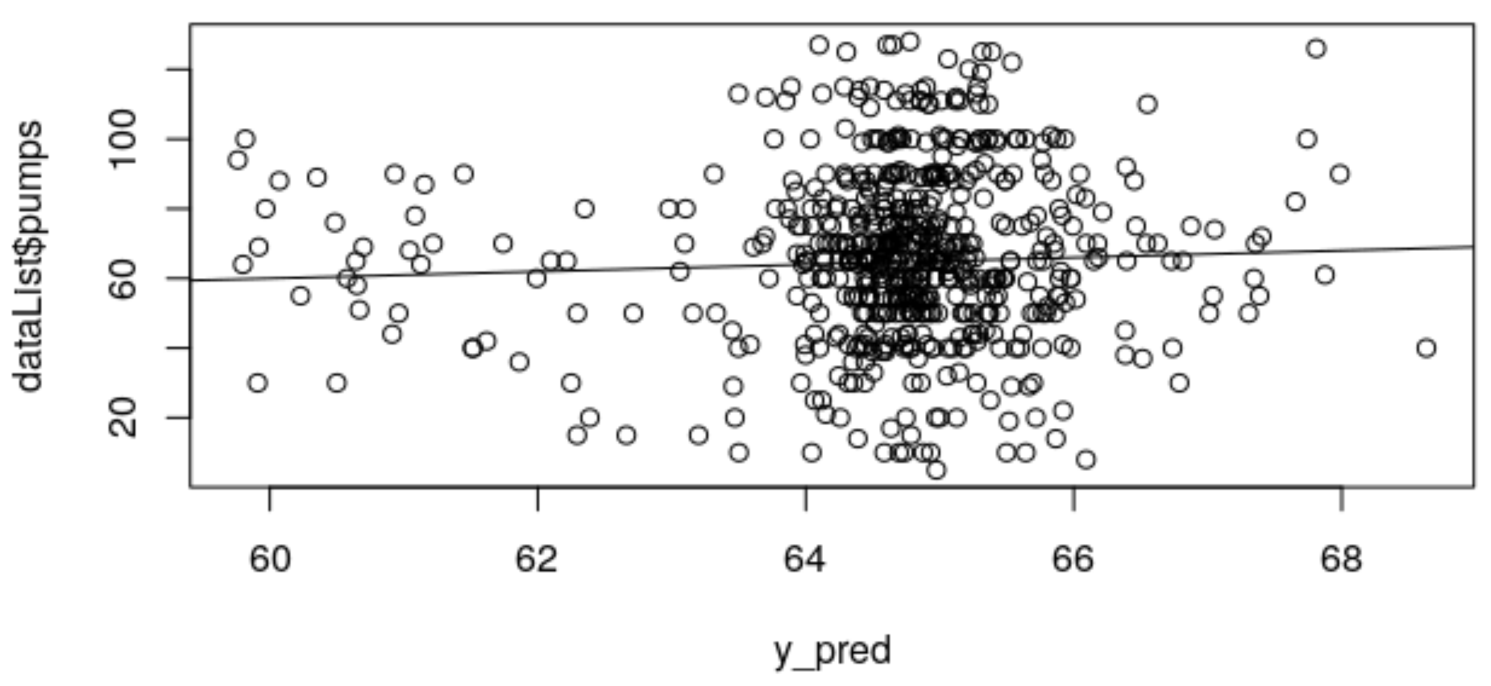
LOOIC & ELPD Value

	Model 1	Model 2	Model 3	Model 4
LOOIC	5824.9	5754.2	5824.0	5824.3
SD	2.1	24.2	1.1	0.2

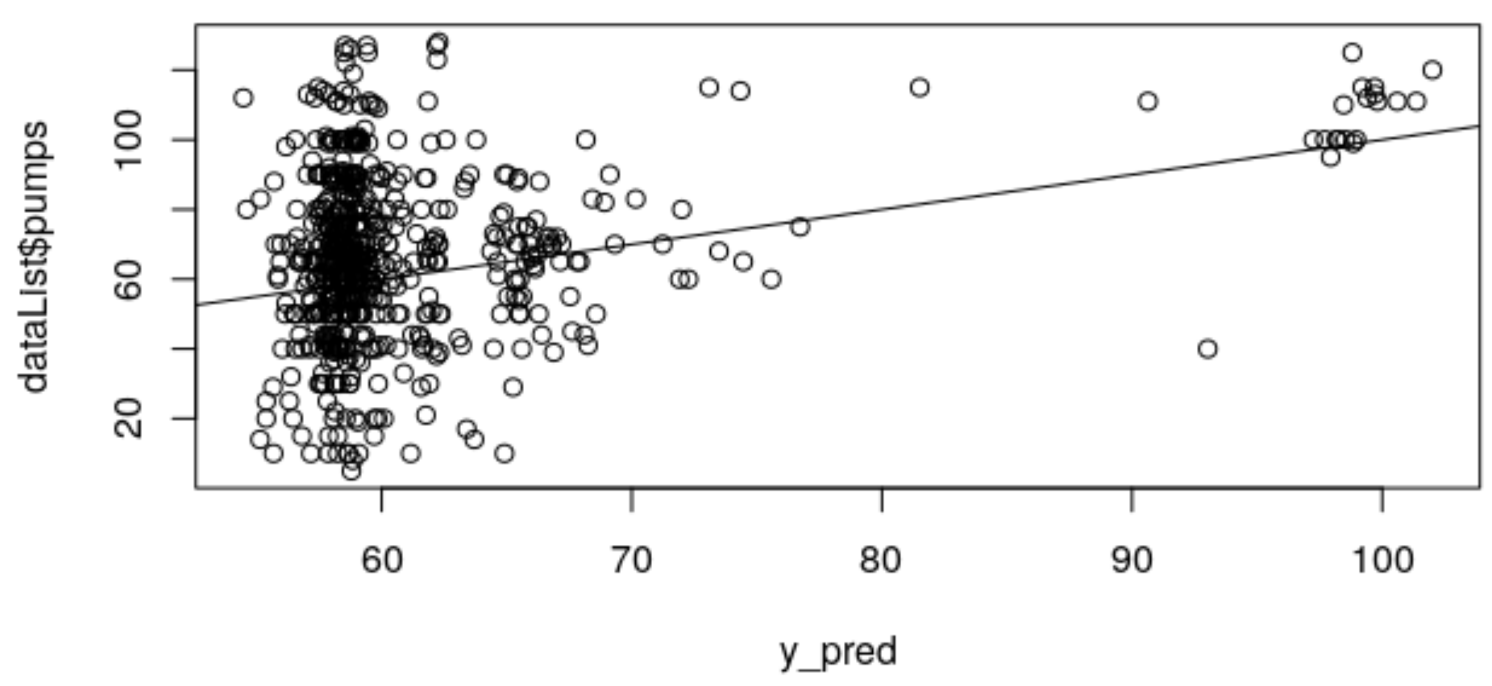
	Model 2	Model 3	Model 4	Model 1
elpd_diff	0.0	-34.9	-35.1	-35.4
se_diff	0.0	12.1	12.1	12.3

Result

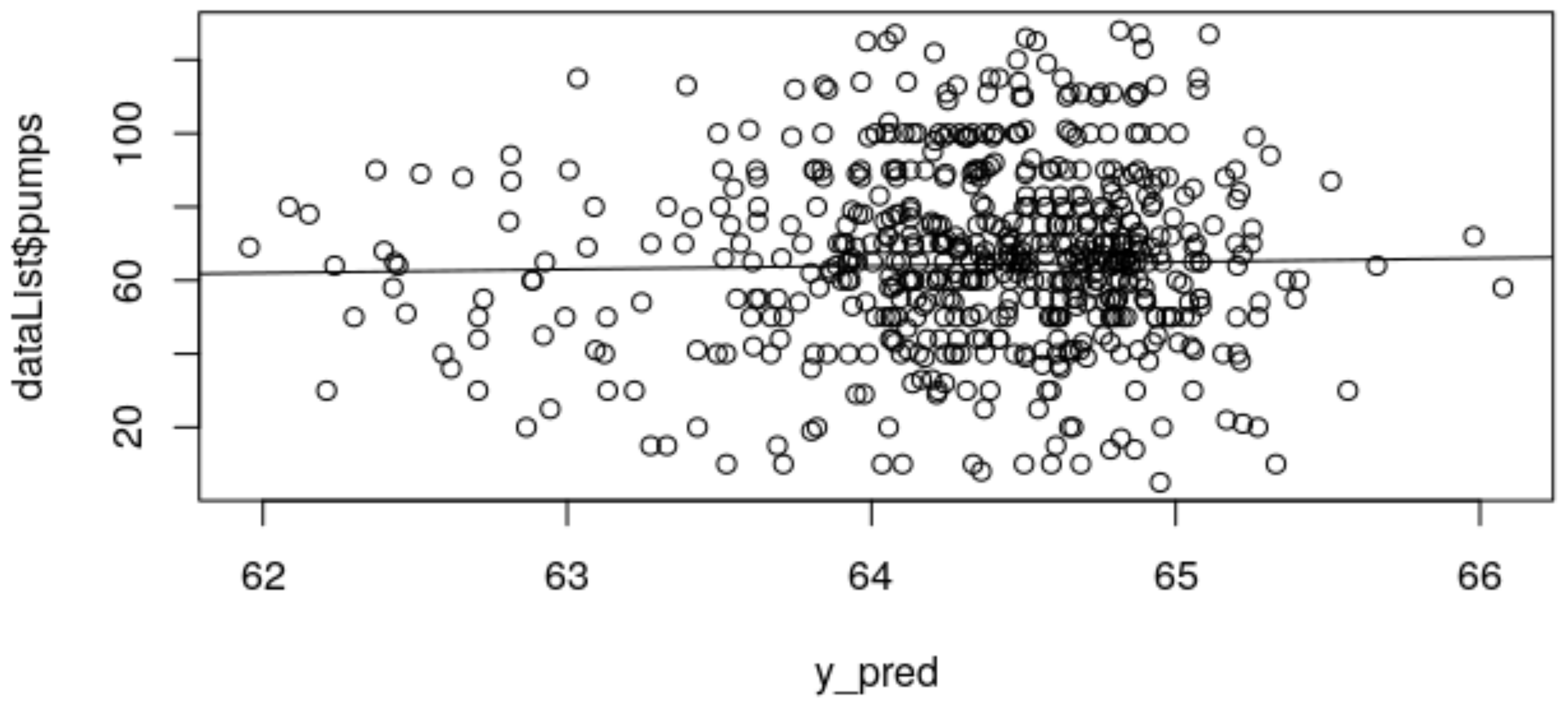
Posterior Predictive Check



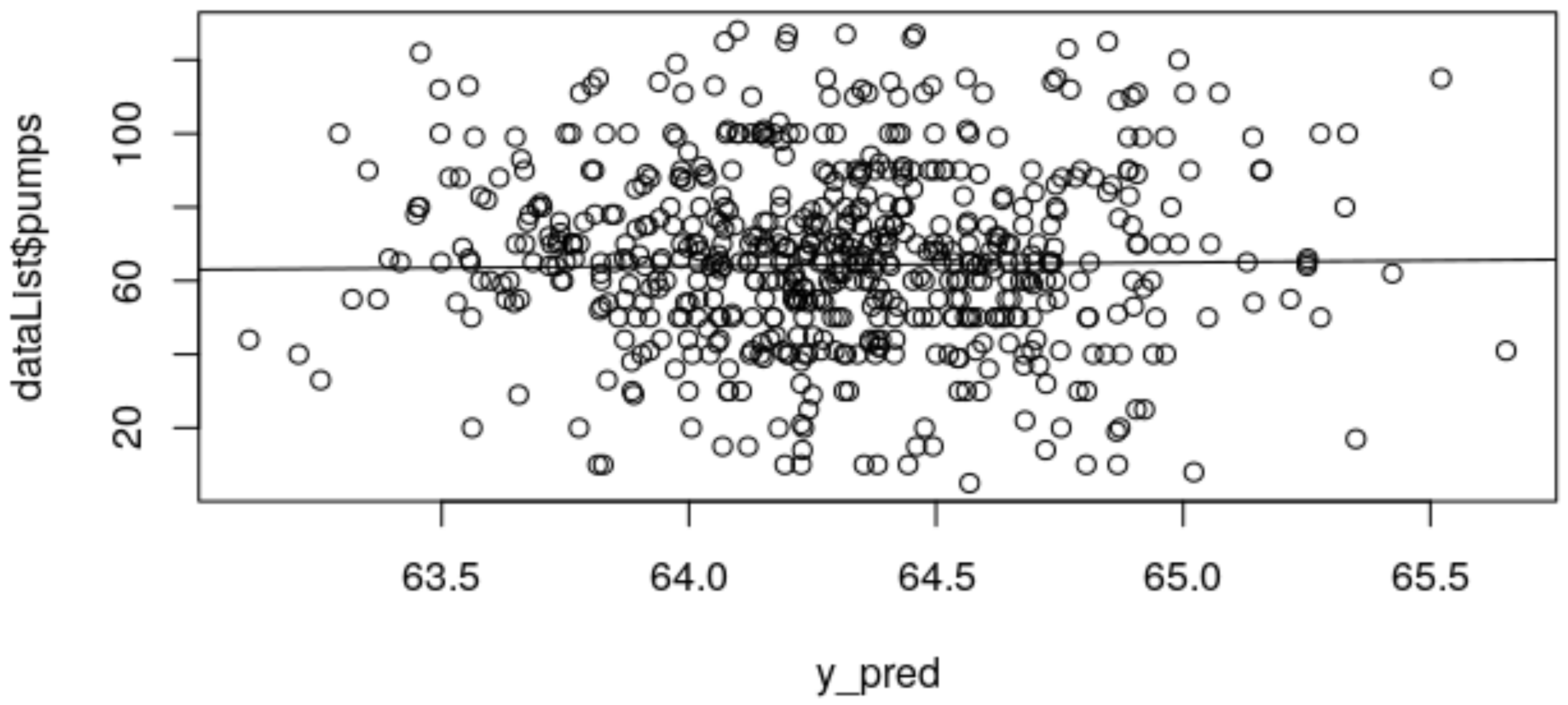
Model 1



Model 2



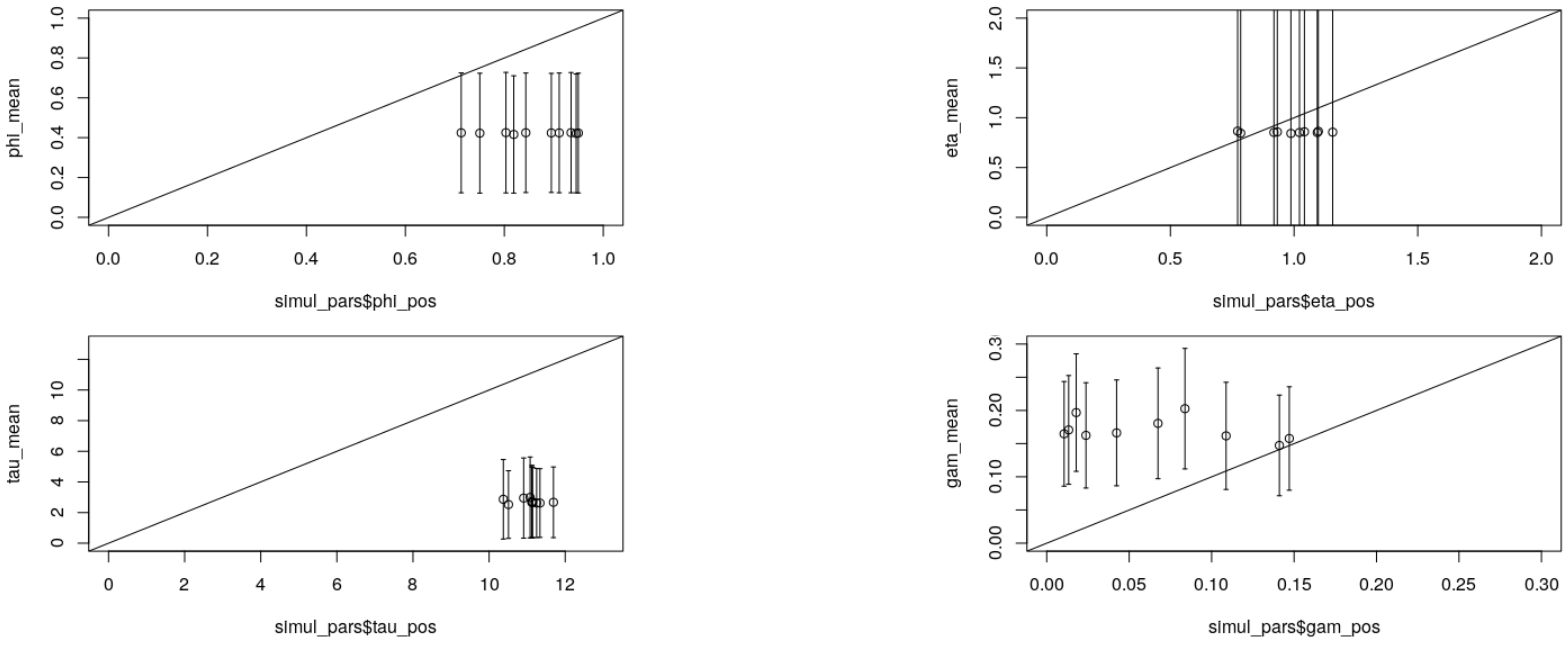
Model 3



Model 4

Result

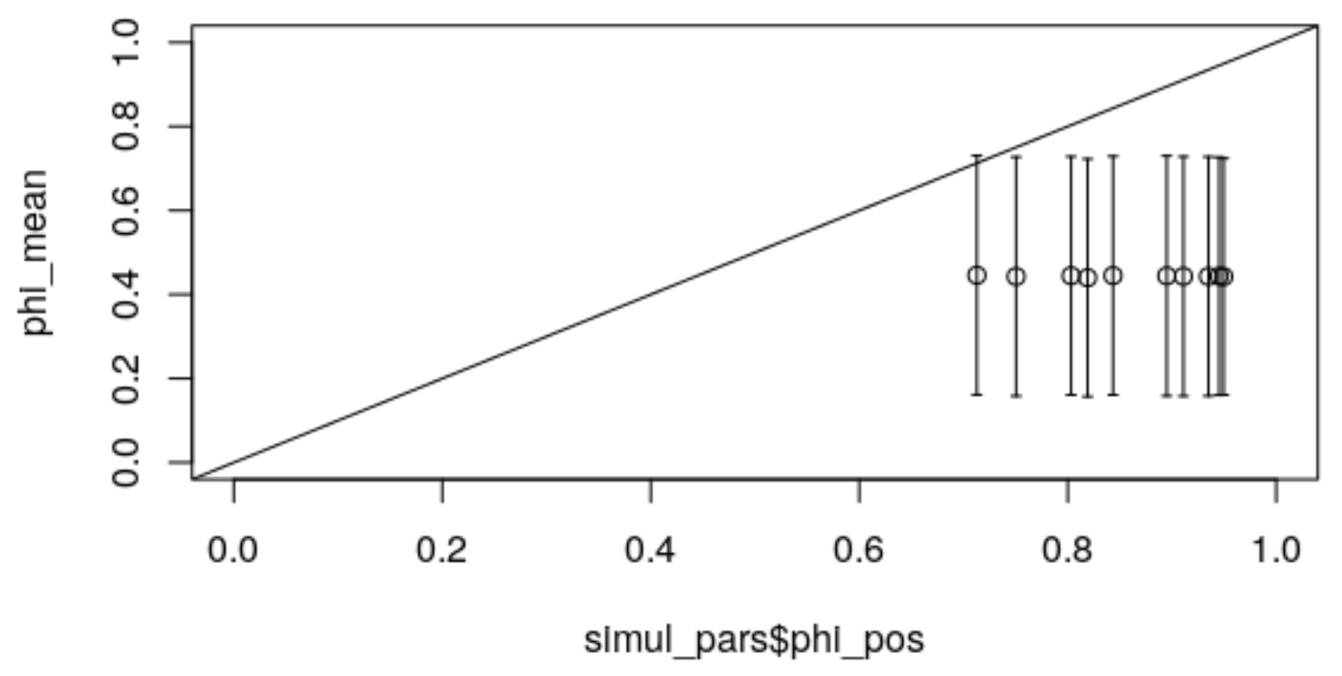
Parameter Recovery of Model 2

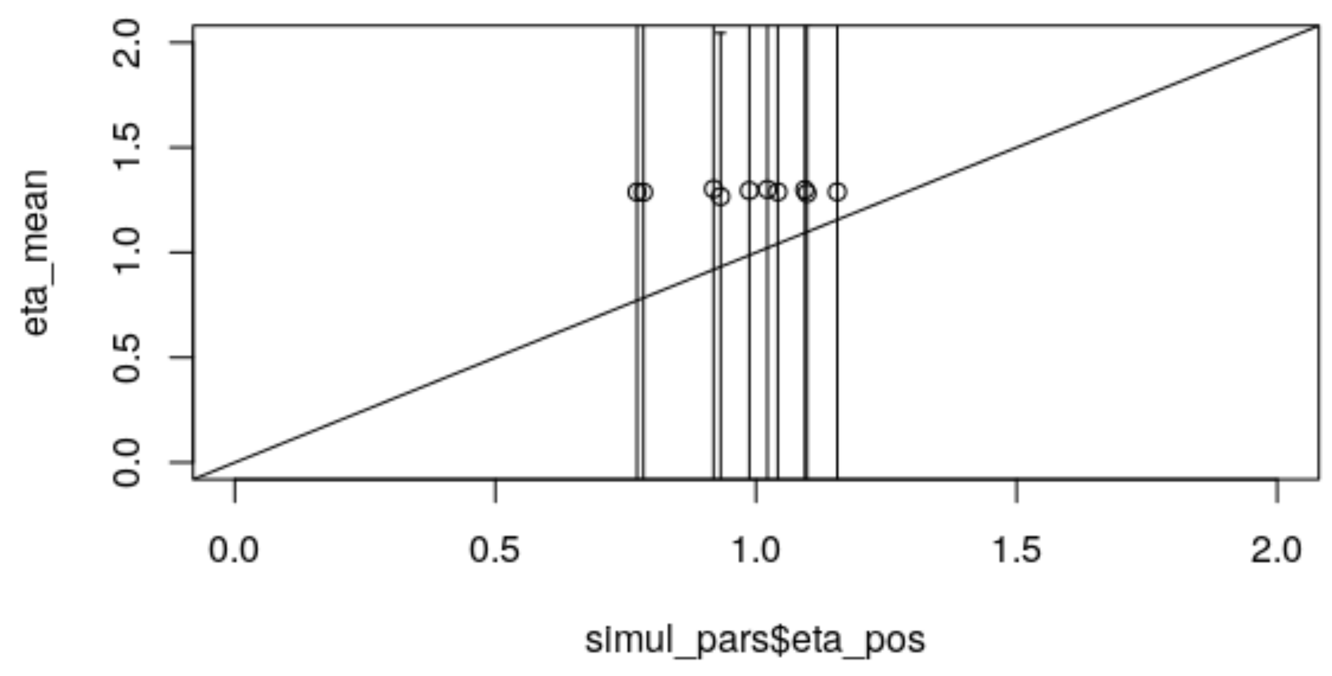


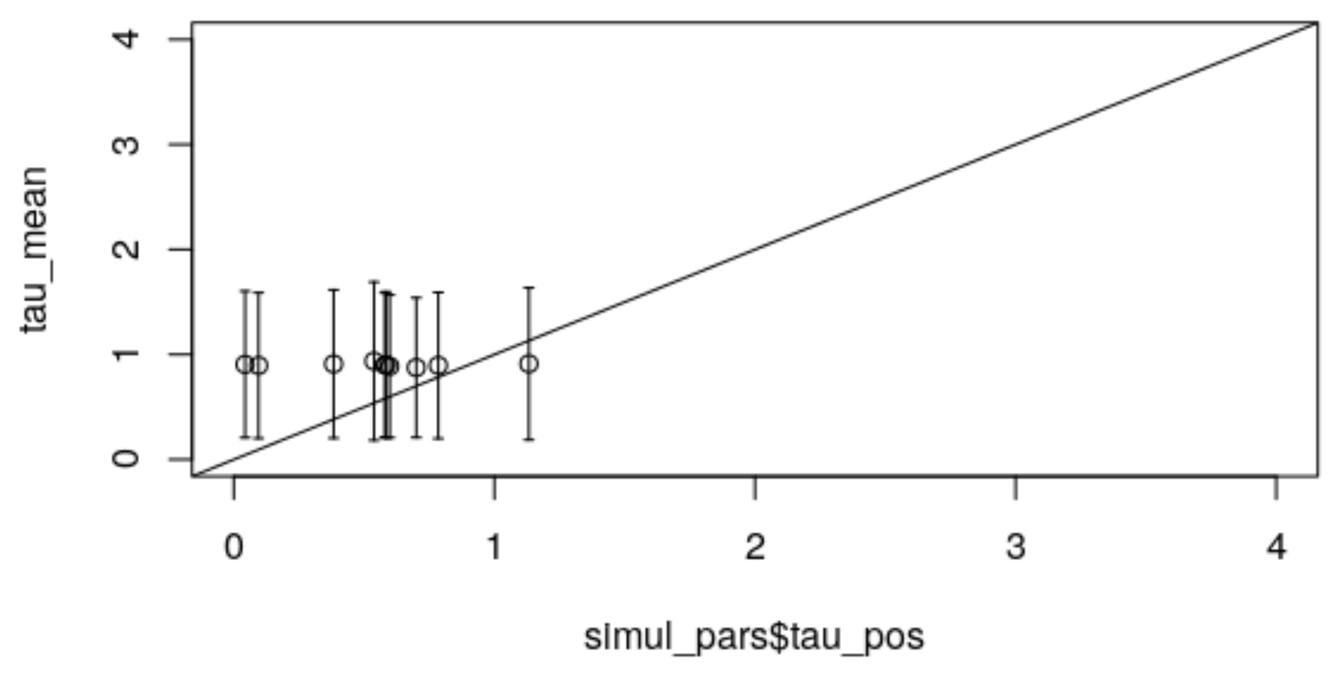
The parameter value of the simulated data were set to the value of the hyper-parameters estimated from the real data.
The simulated data had 10 subjects with 30 trials.

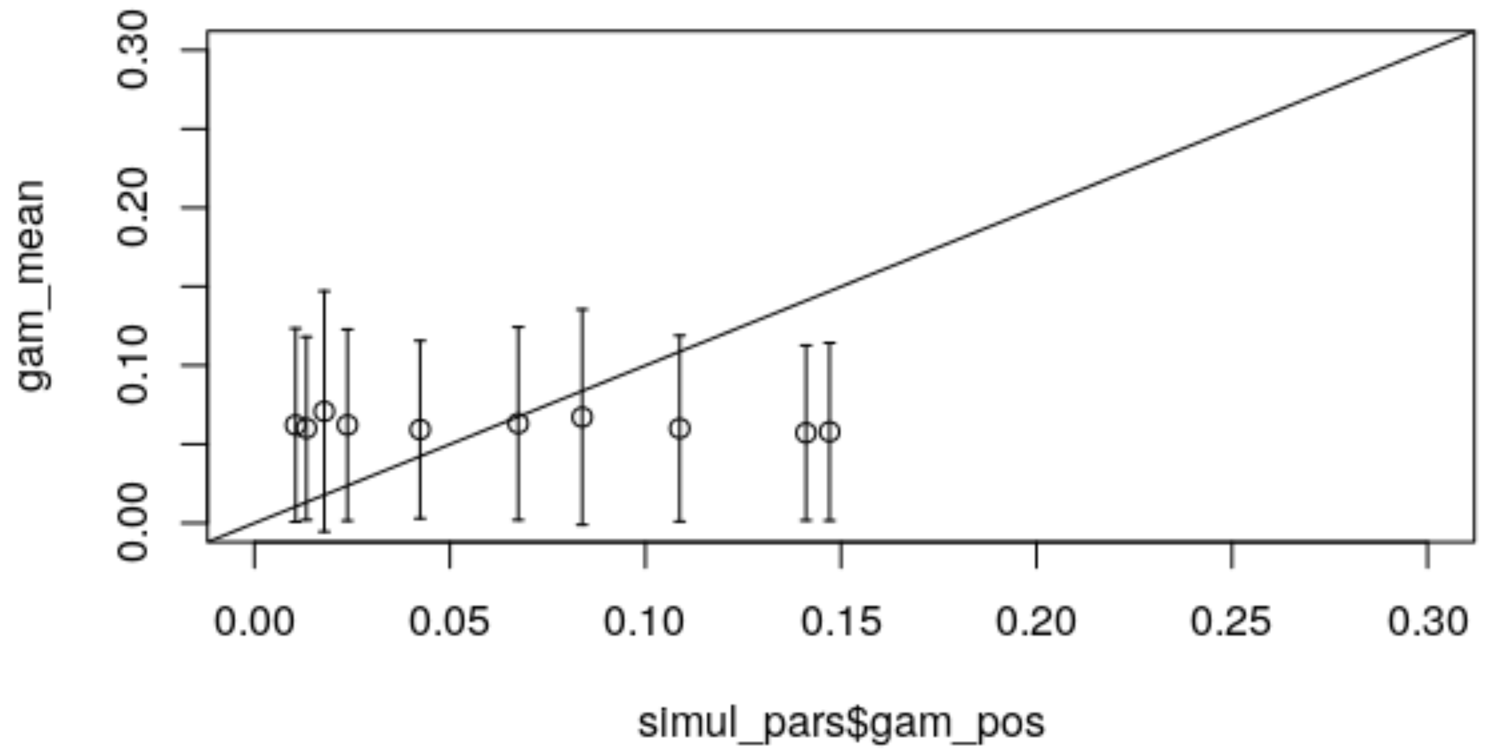
Result

Parameter Recovery of Model 2 (w lower τ value)



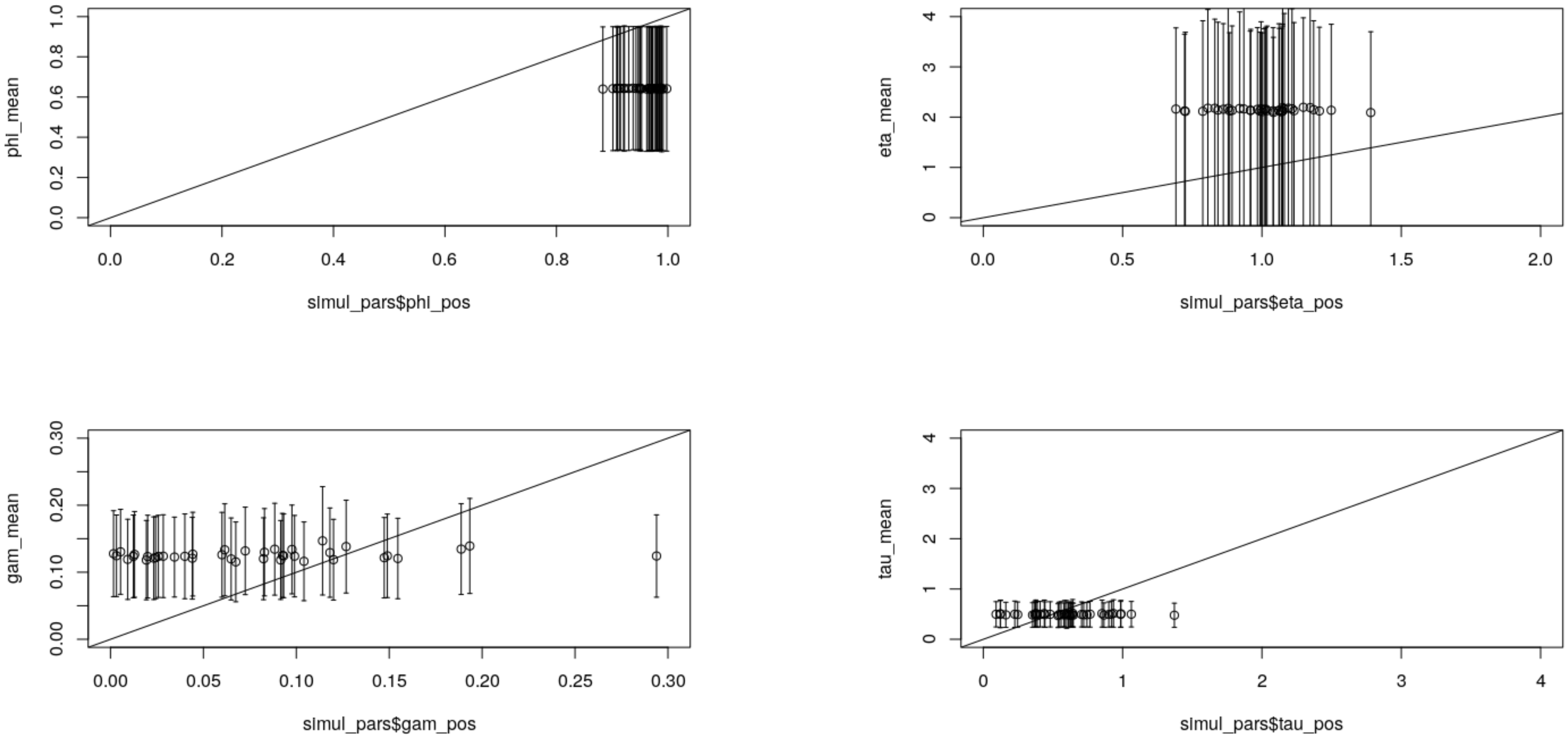






Result

Parameter Recovery of Model 2



Here, more subjects and trials were added: total of 40 subjects, each with 50 trials, were simulated and recovered.

Model Fitting

Maximum Likelihood Estimation

- R is used.
- All models were fitted with the following set-up.

  10 different priors to avoid the problem of local minimum

  Optimized using Limited-memory BFGS algorithm in “optim” method from R

Result for MLE

Parameter Estimation

Each cell shows the mean value of the estimated parameters of all subjects

Model	Model 1	Model 2	Model 3	Model 4
Phi	0.33	0.97	0.33	0.85
Eta	0.40	0.44	0.43	0.45
Gamma	0.62	0.58	0.63	0.57
Tau	0.60	0.49	0.52	0.51

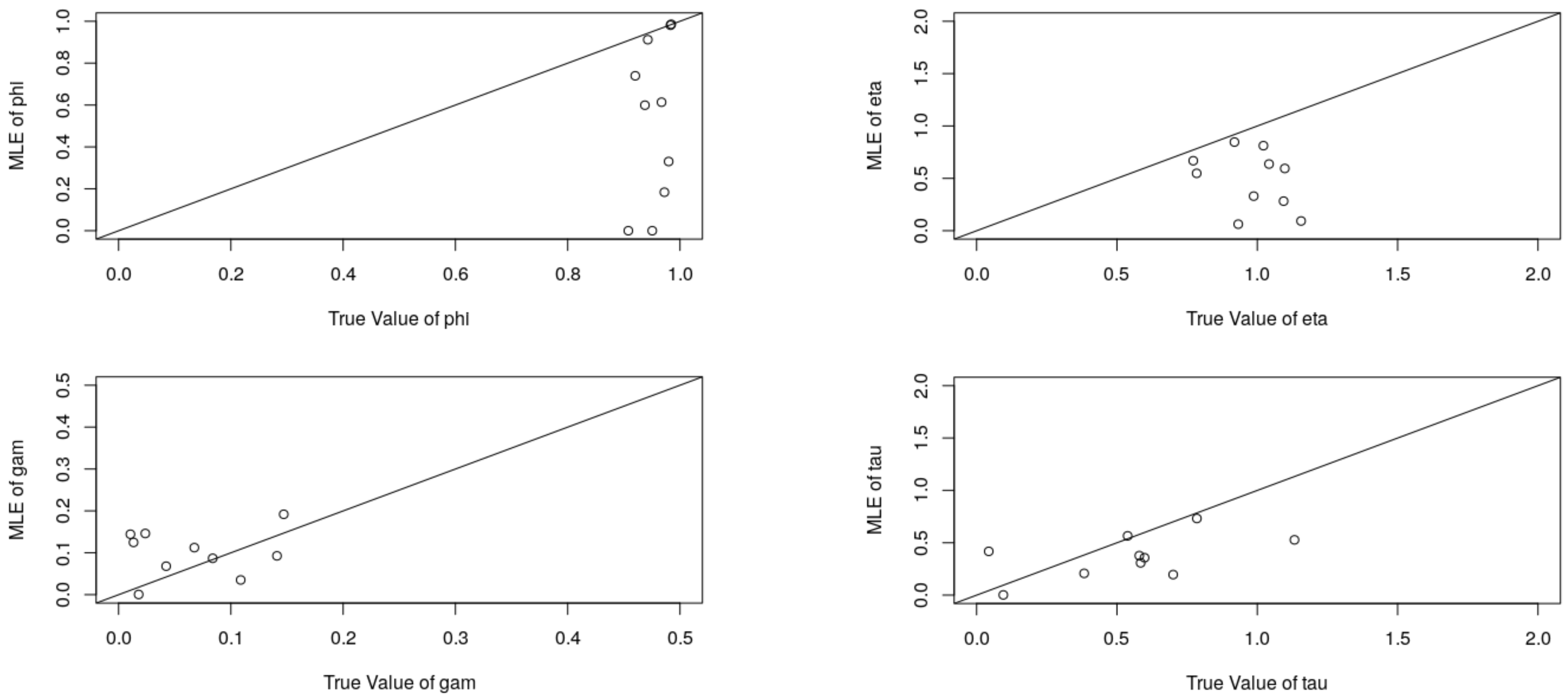
Result for MLE

AIC and BIC value of the Model

	Model 1	Model 2	Model 3	Model 4
AIC	15.701	13.601	15.702	13.694
BIC	15.996	13.896	15.997	13.989

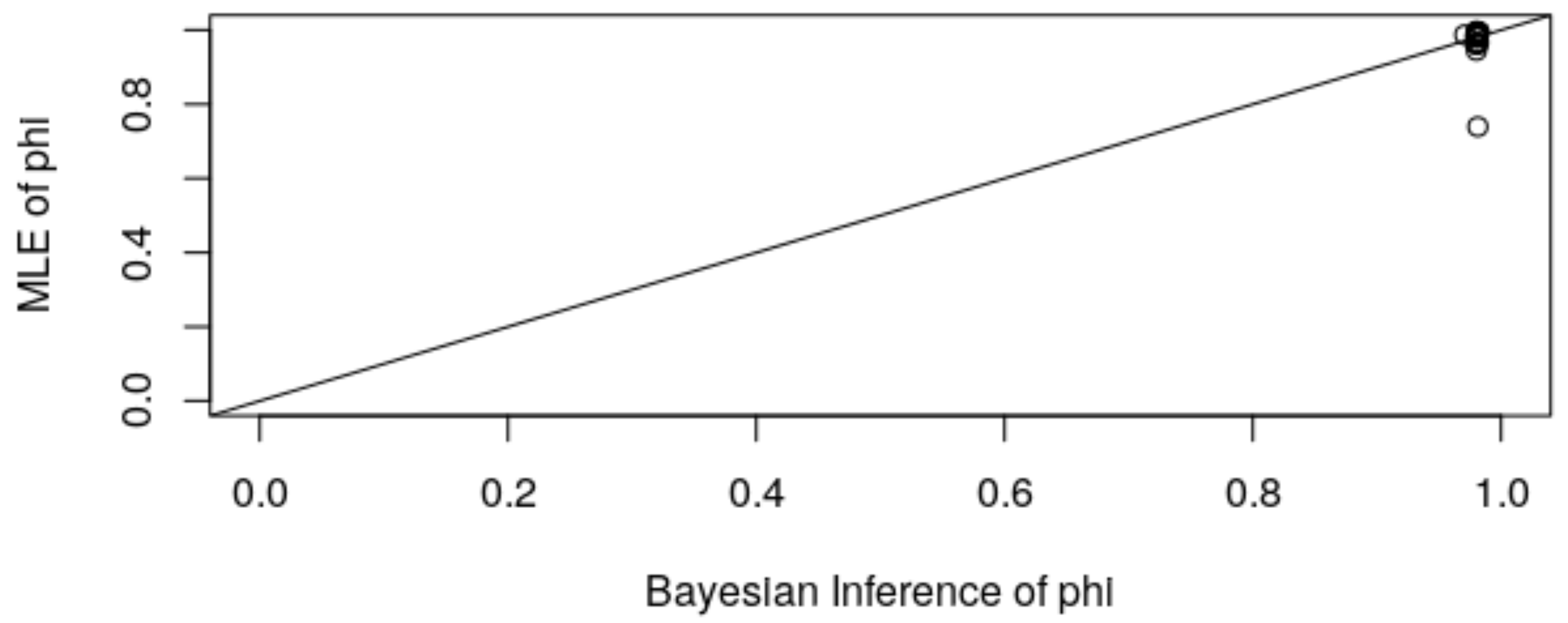
Result for MLE

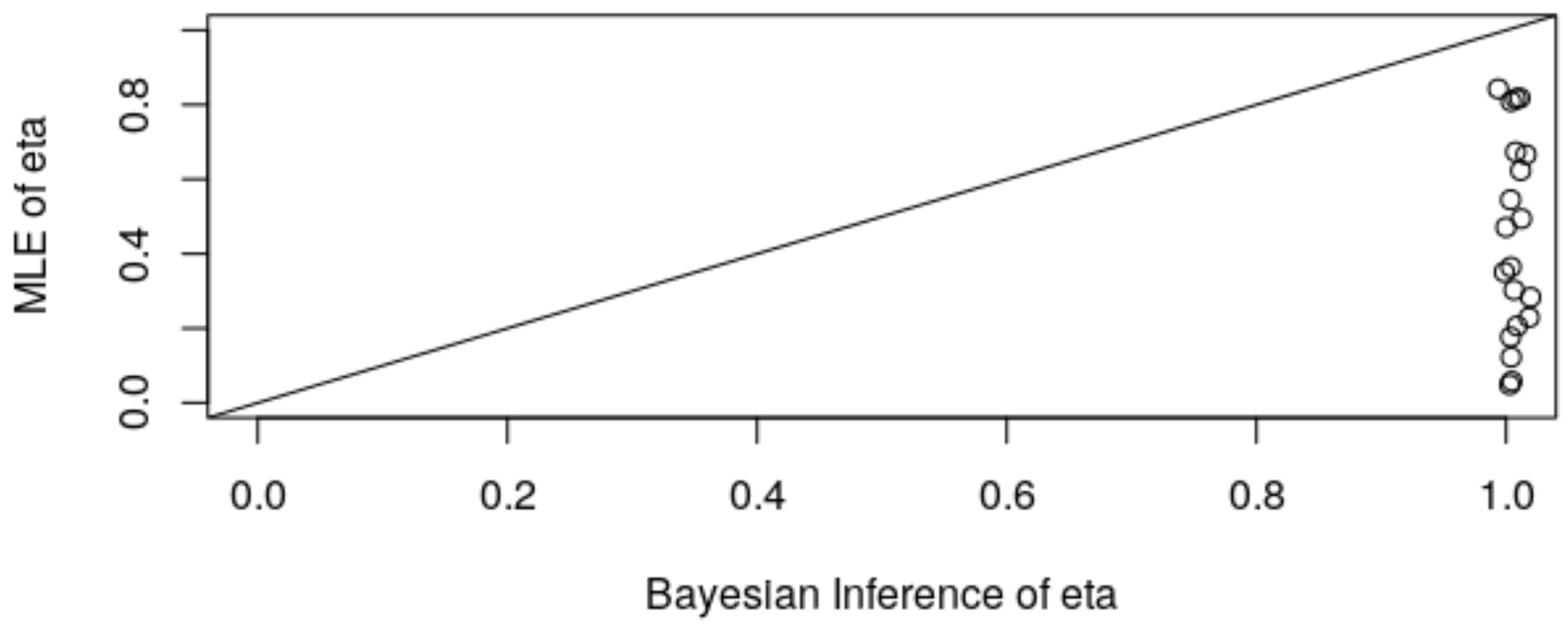
Parameter Recovery of Model 2

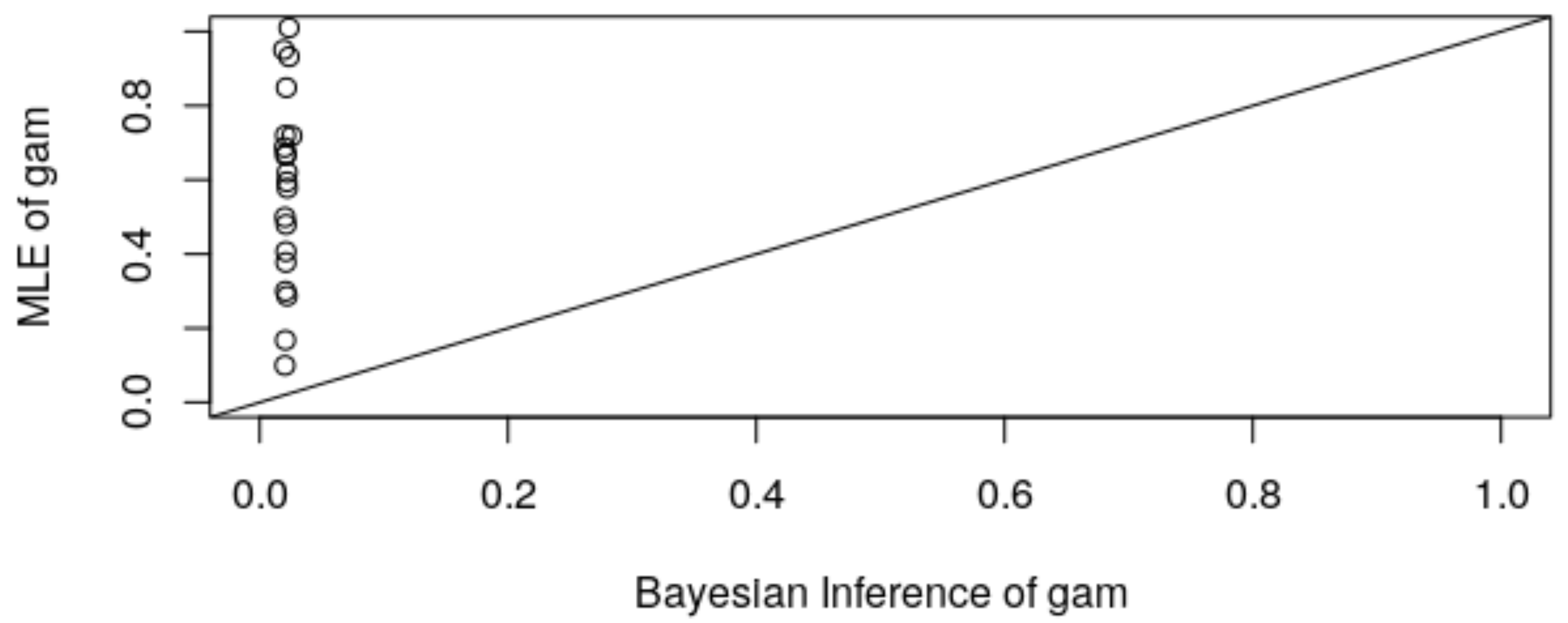


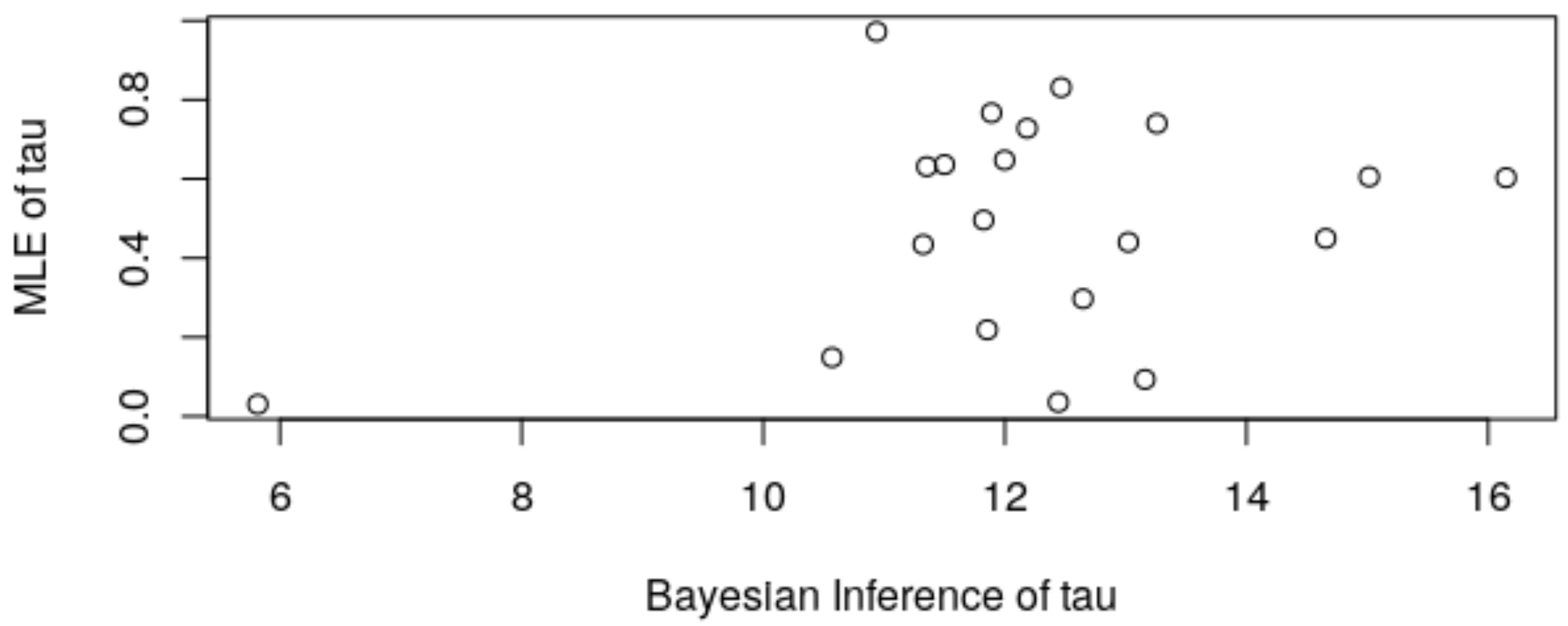
MLE vs Bayesian

Plot of estimated parameter value against MLE and Bayesian









Model Comparison

No Individual difference vs Hierarchal structure

	No Individual Difference	Hierarchal Structure
Phi	0.996 / 1	0.98 / 1
Eta	2.227e-06 / 1	0.98 / 1
Gam	0.781 / 1	0.02 / 1
Tau	0.952 / 1	11.07 / 1

Result

LOOIC of No Individual difference vs Hierarchal structure

Model	No Individual Difference	Hierarchal Structure
LOOIC	5528.7	5754.2
SD	32.9	24.2

Model	No Individual Difference	Hierarchal Structure
elpd_diff	0	-112.7
se_diff	0	14.9

Discussion

Looking at the parameter recovery result done with MLE, it is clear that ϕ and η, parameters related to learning of the participant, are having difficulty being recovered. This seems due to the fact that with BRAT, **the participant does not get the information when the explosion point for the balloon.** In non-automatic BART, if the participant pumps for n times and pops, $\sum n^{success}$ will still increase in value of n - 1. However, for BRAT, because the participant does not get any information, no addition will be made. Therefore, the impact of a single loss is enlarged. For example, if participant's ϕ and η is 0.9 and 1 respectively and pops the balloon on the first trial with 64 pumps (half of what was given), the expected change rate of risk immediately drops to 0.014. Due to this aspect of design, the impact of ϕ is abnormally reduced. I suspect this aspect of the model to be the crucial reason for failure in recovery.

Conclusion

Out of the four models under investigation, **Model 2** —which assumed a participant 1) measures the risk based on how much he decided to avoid, rather than to take and 2) views the task as gain-only situation — showed the lowest LOOIC score, showing a 3 standard deviation difference with the next competitive model. When fitted using MLE and compared with BIC and AIC, Model 2 consistently showed better performance.

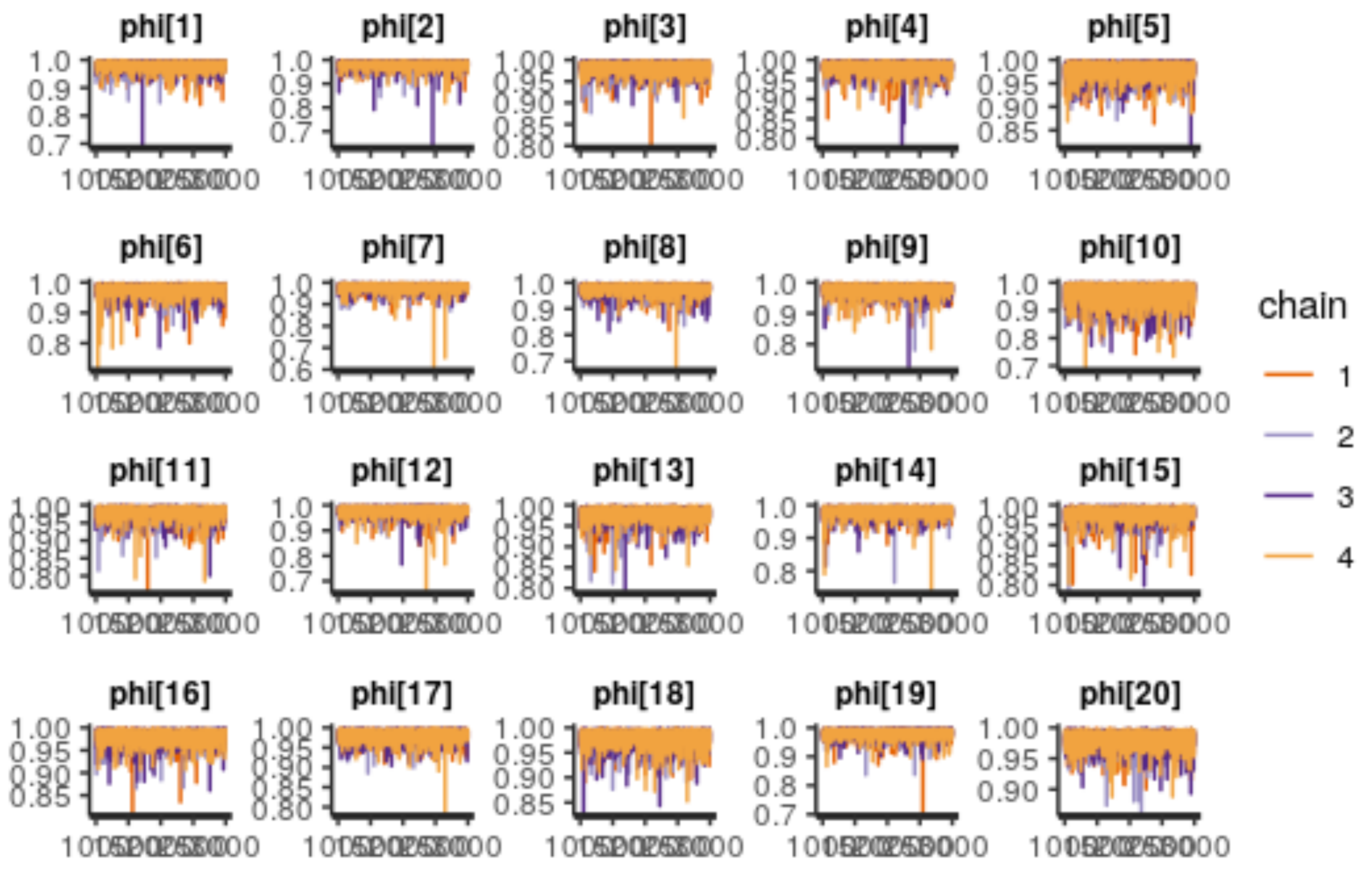
However, Model 2 showed **very poor parameter recovery**. Especially when fitted with Bayesian Hierarchal structure, the recovered parameter showed a sign of dramatic shrinkage, failing recovery. It performed relatively better with MLE parameter recovery, although ϕ and η continuously was not recovered well. **The learning aspect of the model seems to be in need of improvement.**

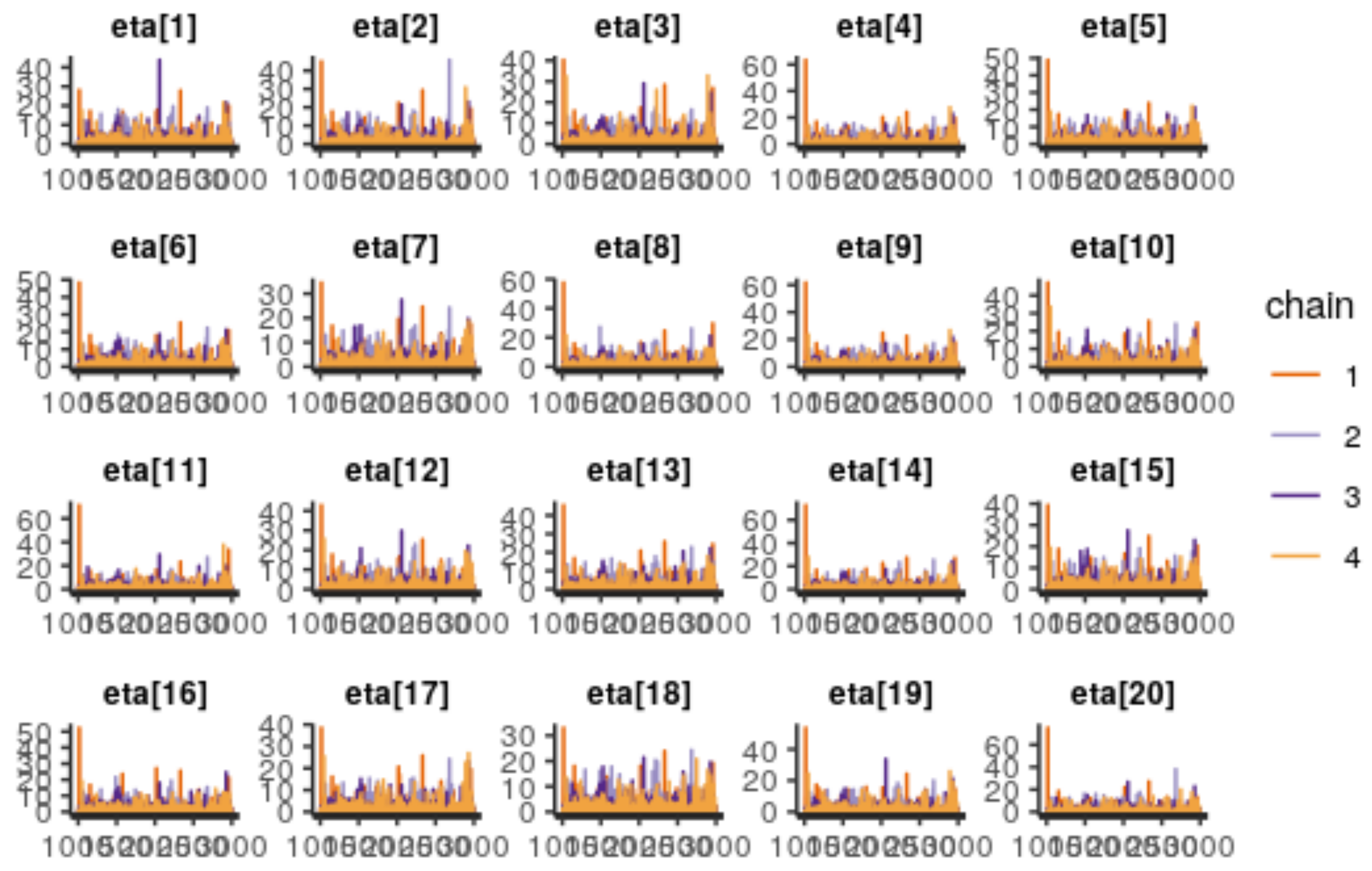
Reproducibility

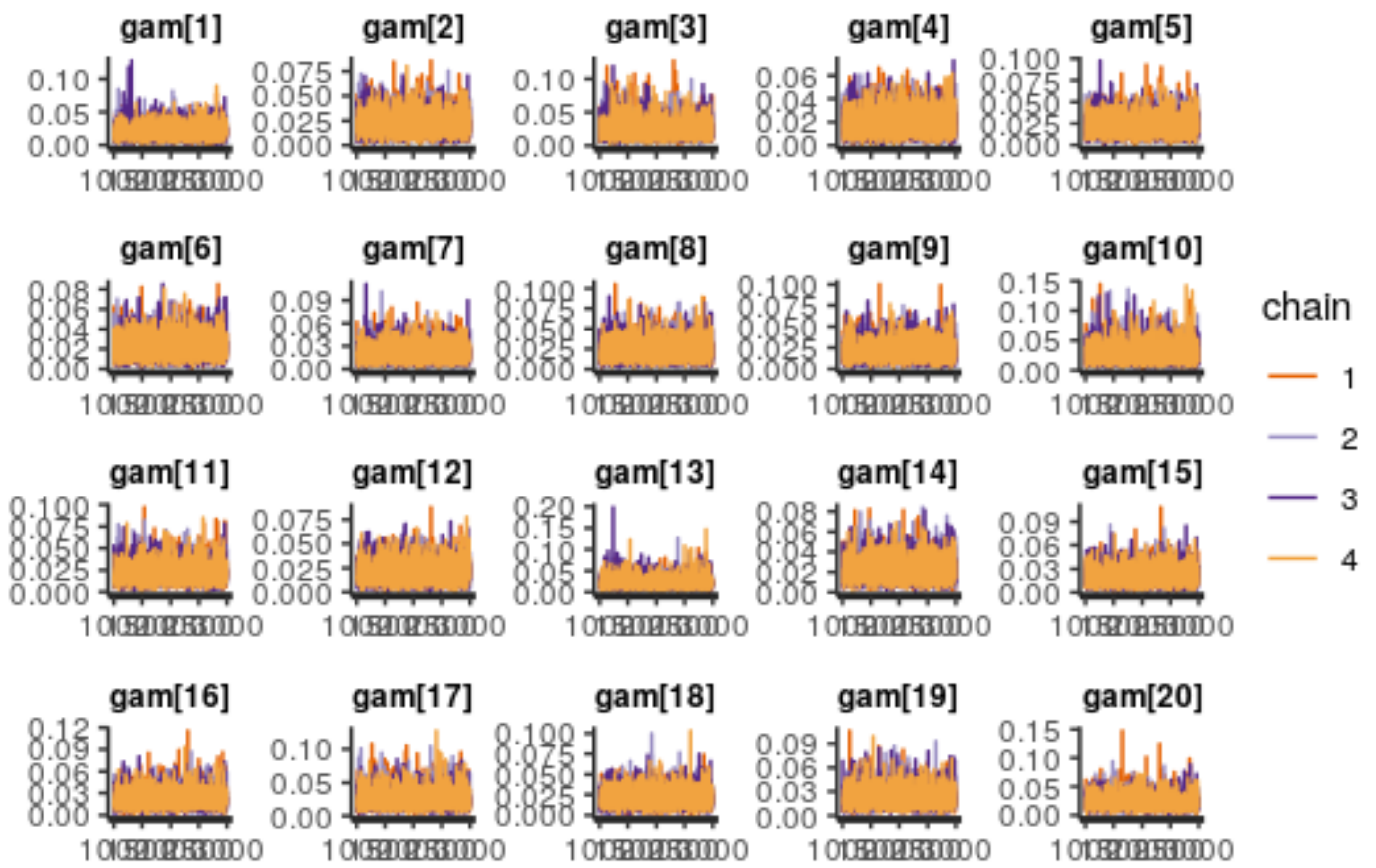
- All fitted samples using Stan are saved in rds file.
- All R files simulating the data and the simulated data in txt format are saved under the folder “Parameter Recovery.”
- All fitted samples using MLE are saved as RData file.
- “export_brat_time1(n=20).txt” is the raw file. “export_brat_time1(n=2).txt” is the shortened version of the data with two participants, used during testing.
- All the rds files and RData files are uploaded in the following google drive link
    - https://drive.google.com/drive/folders/1cJxSAHb5jXYjsMx_jdXLJ7BTp9UwtCVV?usp=sharing

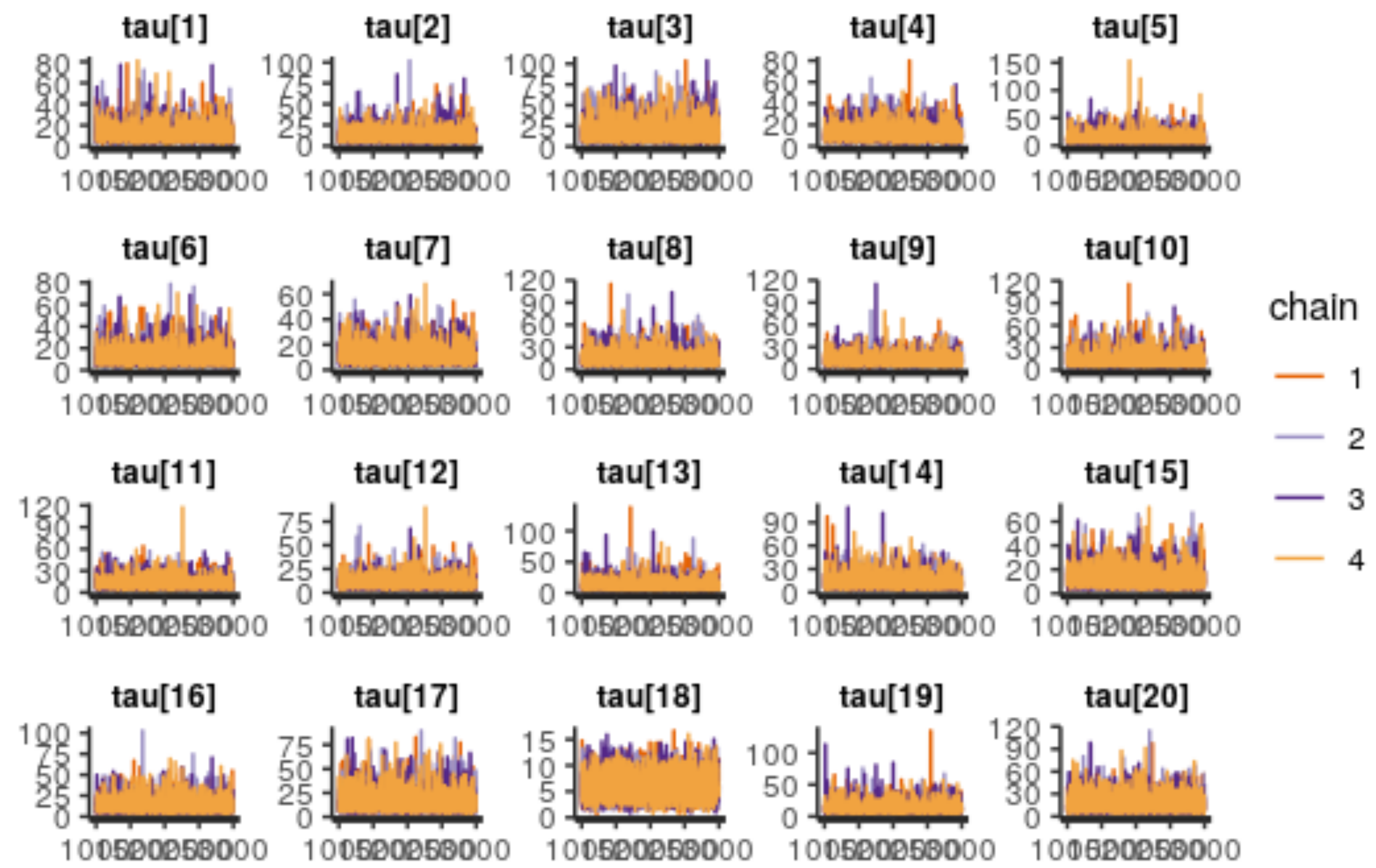
Appendix

Trace plot of Model 2



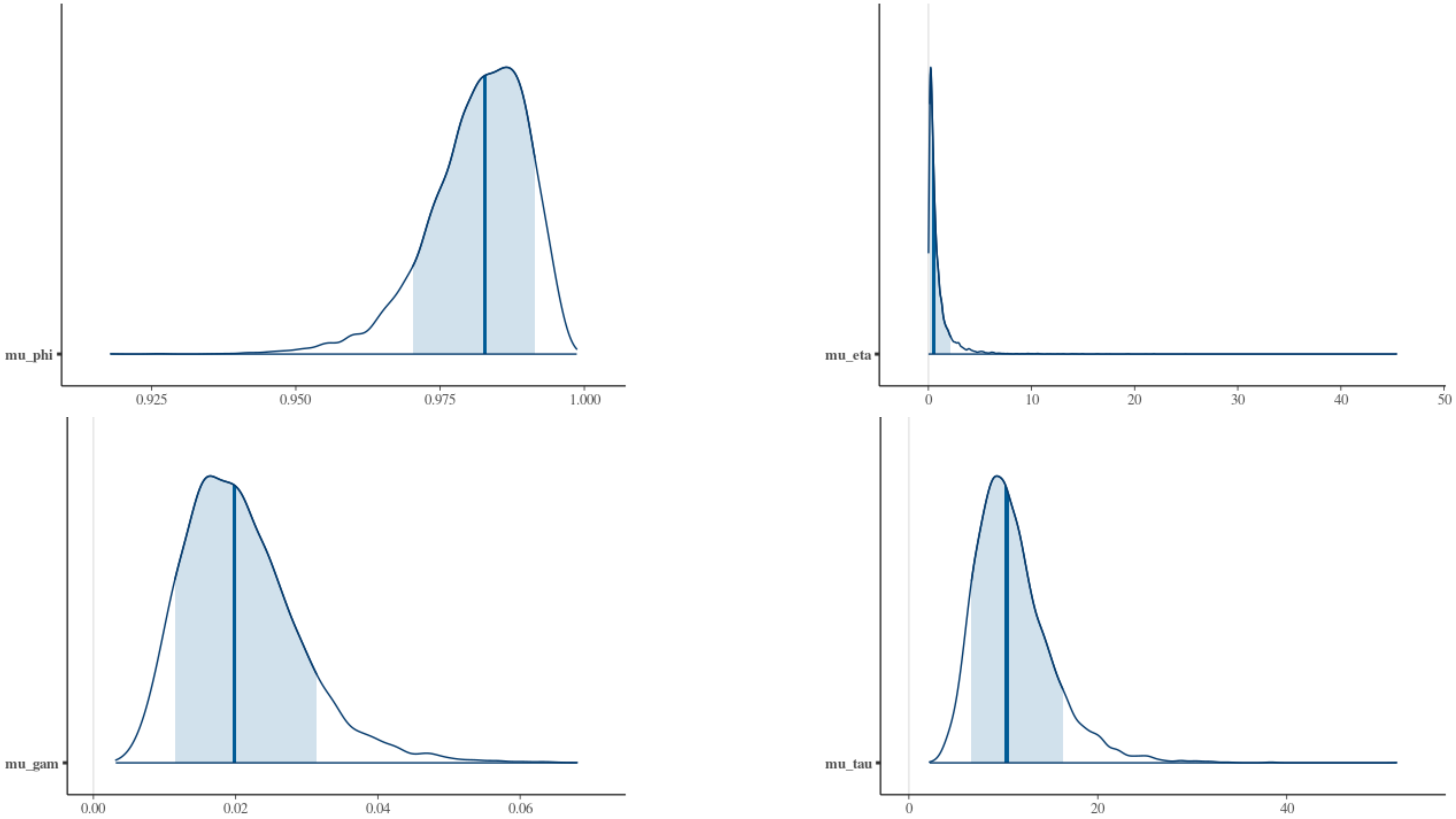






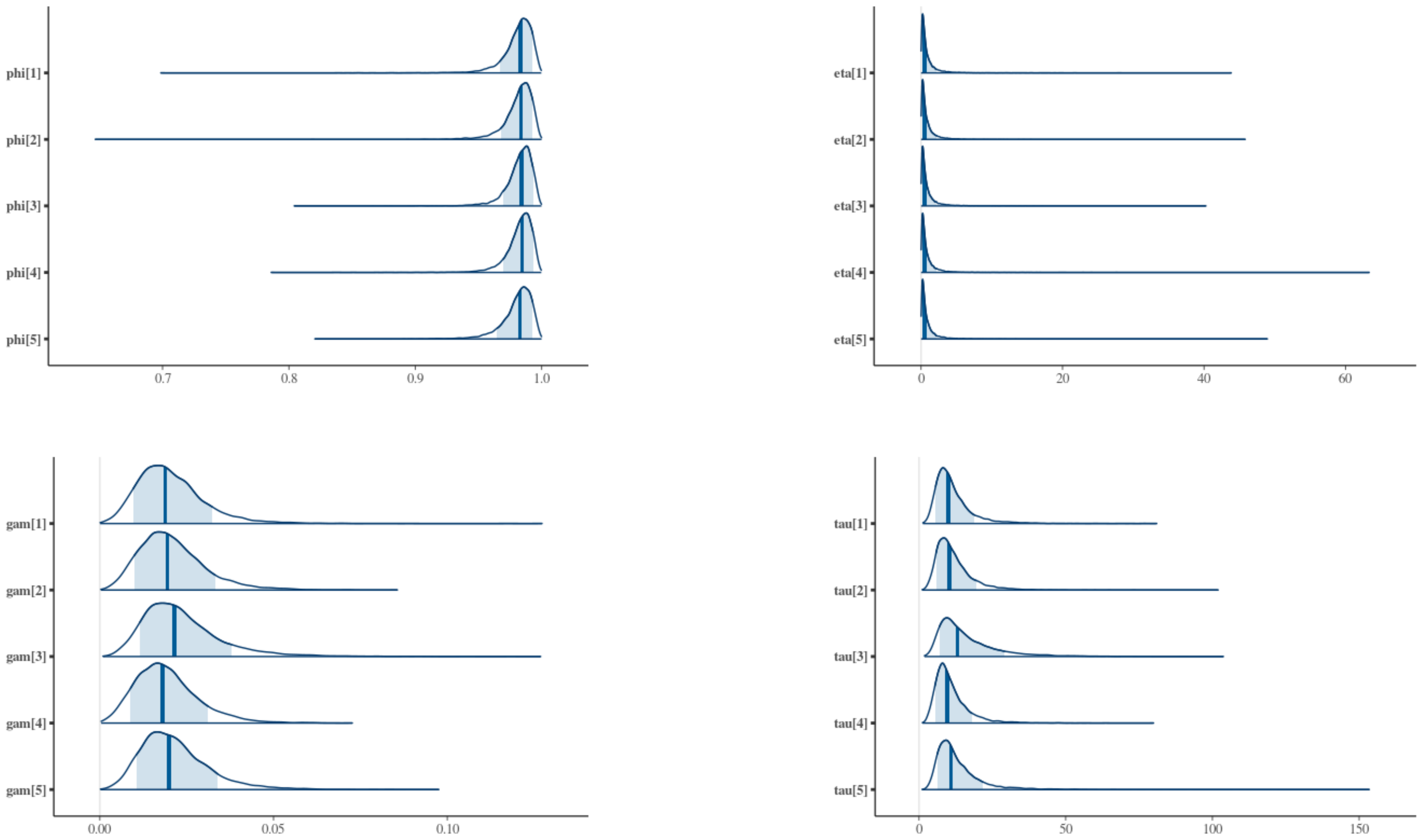
Appendix

Posterior Distribution of Model 2 (Group-level parameter)



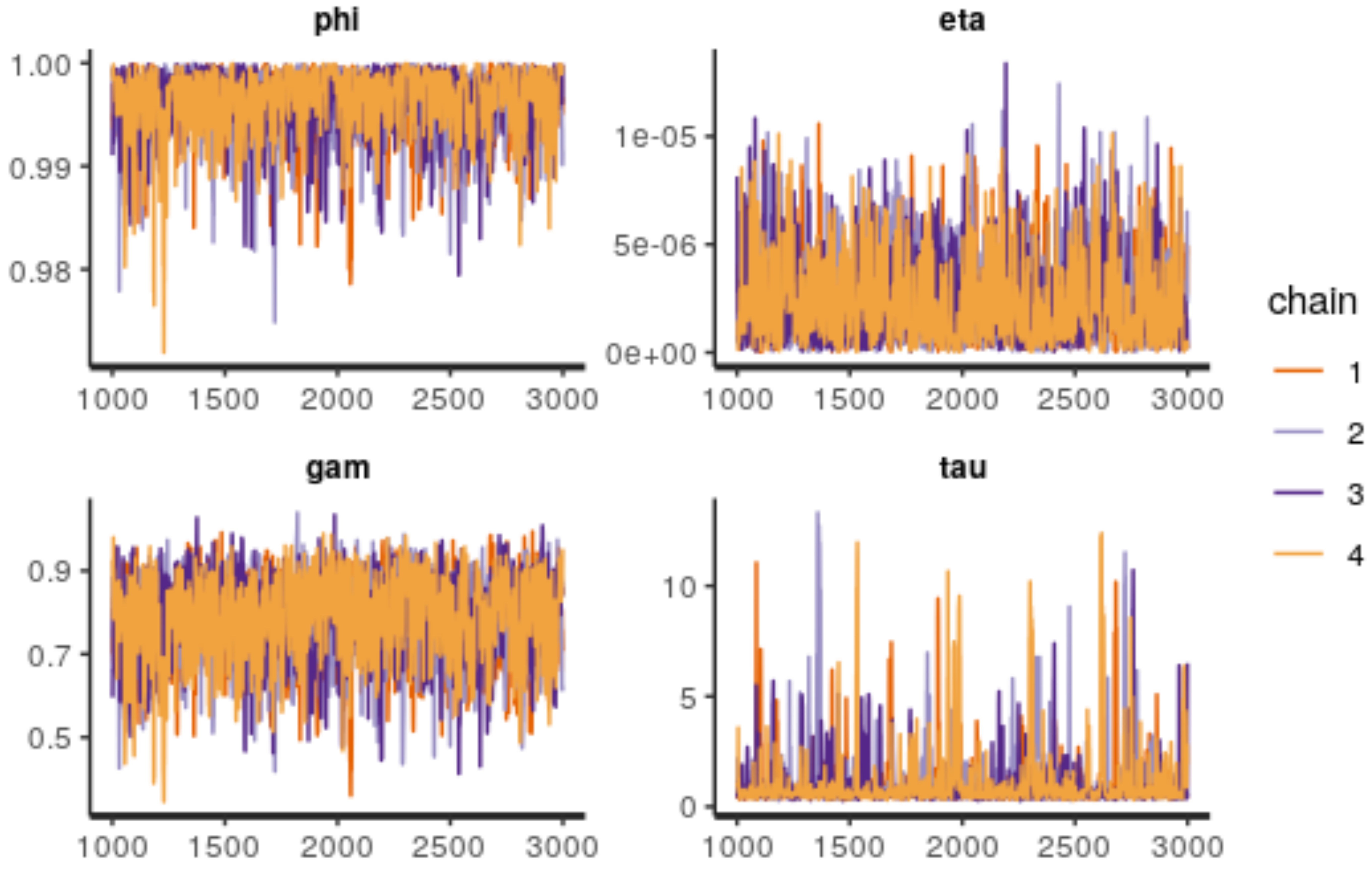
Appendix

Posterior Distribution of Model 2 (Individual parameter of first 5 participants)



Appendix

Trace plot of Model 2 assuming no individual difference



Appendix

Posterior Distribution of Model 2 assuming no individual difference