Modeling Happiness: Modulation by Depression

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Computational Modeling Term Project

Abstract

Unlike widely understood Reward Prediction Error (RPE) theory of happiness, recent studies suggests learning-related variables explains happiness. This highlights the need for new models that incorporate such variables. Furthermore, these models enable assessment of the influence of depression on the relationship between learning and happiness.

In the present study, we employed a two-armed bandit task with sporadic happiness reports and applied computational modeling techniques. The analysis was conducted with data consists of 75 participants with 160 trials and 46 reports on happiness. We compared original and modified happiness models using several sets of variables. To examine the influence of depression on sensitivity to variables, we divided each coefficient to group mean and variance(β_PPE and $\beta_P$hat) by BDI-II value.

Model comparison based on LOO reveals that the model incorporating subjective expectations and learning-related prediction errors exhibited the best fit. However, no significant effect of depression was observed on parameter sensitivity.

These findings provide insights into the mechanisms of happiness in learning environment, emphasizing that high expectation and better-than-expected outcomes serve as strong cues on happiness. Further research should investigate these variables in relation to emotional traits such as depression.

Reward Prediction Error

: Core concept in Reinforcement learning and Affective Neuroscience

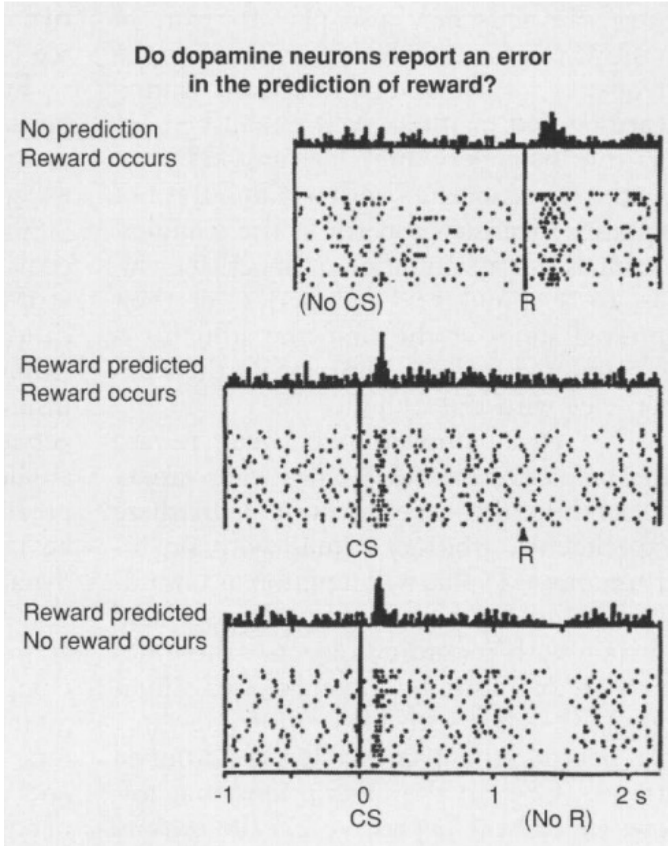
Reward Prediction Error, rather than Rewards, induces dopamine

- Dopamine Firing in dopaminergic neurons (VTA, SNc): RPE > Reward
- RPE → Dopamine → Hedonic Reaction (e.g. liking, pleasure)

Happiness is summation of Momentary happiness

- Life satisfaction = Integral of momentary happiness

(Kahneman et al., 2004)



(Schultz et al., 1997)

Happiness Model

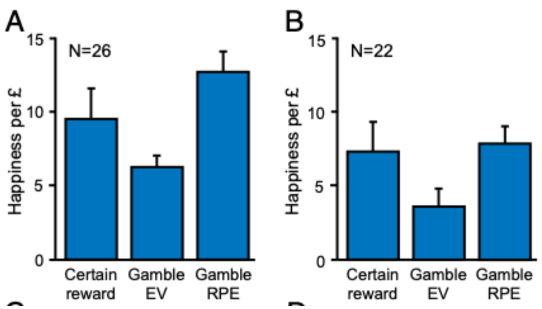
Happiness Model with Reward Prediction Error

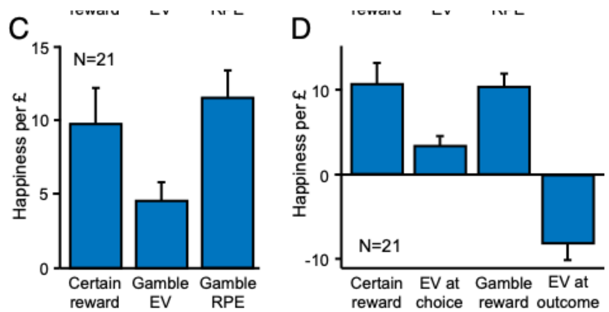
- Weighted Sum of Certain Reward, Expected Value, and Reward Prediction Error
- Decay sum based on trials: Integration on time

$$\mathrm{Happiness}_t = w_0 + w_{CR}\sum_{j=1}^{t}\gamma^{t-j}\mathrm{CR}_j + w_{EV}\sum_{j=1}^{t}\gamma^{t-j}\mathrm{EV}_j + w_{RPE}\sum_{j=1}^{t}\gamma^{t-j}\mathrm{RPE}_j$$

(Rutledge et al., 2014)

Estimation results match well with RPE theory





New Variables

(1) Probability Prediction Error

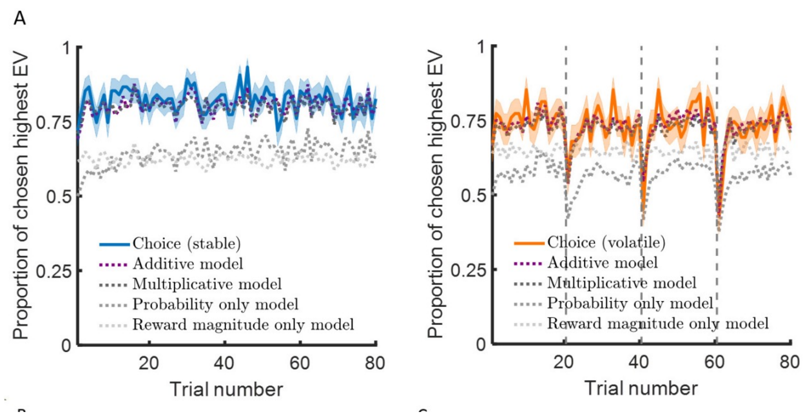
- Happiness ≠ Function of reward received (Learning-irrelevant)
- Happiness = How well they learn and predict outcomes (Blain & Rutledge(2020), Heffner et al.(2021))

(2) New variables: Phat and PPE (Blain & Rutledge(2020))

- Phat: Subjective winning probability updated propotionally to PPE
- PPE: Outcome (0, 1) minus Phat

(3) Additive vs. Multiplicative Models

- Additive: Summation of Probability and Reward difference
- Multiplicative: Based on Expected Utility Theory
- Additive model predicts happiness better



1^{st} Aim

1) Develop new happiness models
2) Apply Hierarchical Bayesian approach to each model

- Utilize phat, rather than absolute winning probability of each option
- Set Phat and PPE as separate variables to design additive models
- Compare coefficients and discover the most effective variable

$$\mathrm{Happiness_t} = \mathrm{w_0} + \mathrm{w_{CR}} \sum_{\mathrm{j=1}}^{\mathrm{t}} \gamma^{\mathrm{t-j}} \mathrm{CR_j} + \mathrm{w_{EV}} \sum_{\mathrm{j=1}}^{\mathrm{t}} \gamma^{\mathrm{t-j}} \mathrm{EV_j} + \mathrm{w_{RPE}} \sum_{\mathrm{j=1}}^{\mathrm{t}} \gamma^{\mathrm{t-j}} \mathrm{RPE_j} + w_{PPE} \sum_{j=1}^{t} \gamma^{t-j} PPE_j$$

Depression & Learning

Literature Gap: Underexplored Relationship

- Emotional/neural trait & Happiness: Underexplored (Richter et al.(2014))

Depression and Impaired Learning

- Emotional Decision Making Tasks (Heffner et al., 2021):
  - Individuals with depression: Impaired usage of Emotion Prediction Errors
  - Decision Task: Blunted sensitivity to EPE, slower emotional learning
- Such a significant impairment given the relationship between learning and happiness
  - "Happiness is determined by learning factors of the task" (Blain & Rutledge, 2020)

2^{nd} Aim

Hypothesis: Depression alters how each variable influences behavior

1. Lower sensitivity to PPE (learning-related factor)
2. Negative impact of subjective expectation
    - Predictability of Phat may have less or negative impact to happiness for the depression group

- Also, the inconsistency on the relationship between expectation and happiness can be resolved.
    - Rutledge(2014): “High expectation lowers happiness”
    - Blain(2020): Phat, estimated winning probability, can enhance happiness

Dataset

Blain&Rutledge(2020)

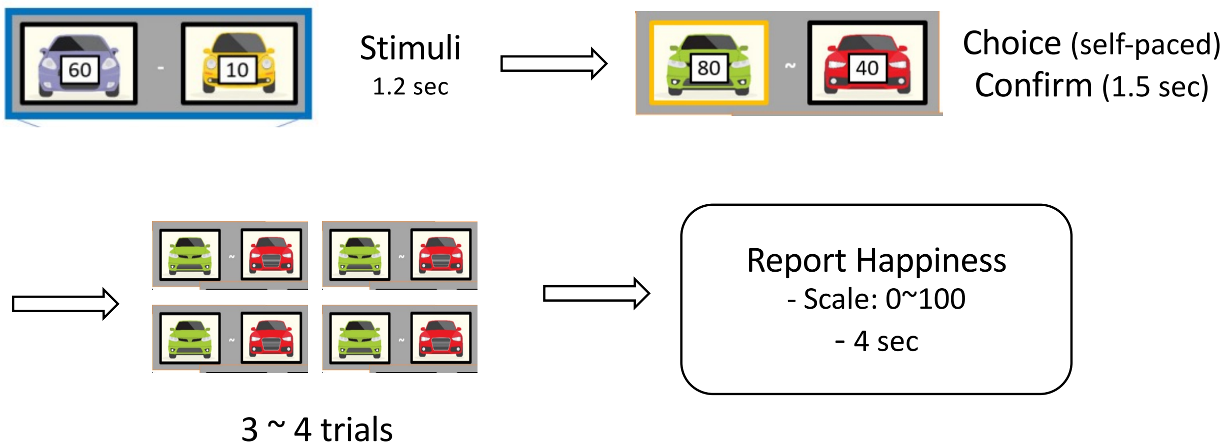
X 75

(Two conditions)

X 160

Task Overview

- 160 trials: Instructed existence of two conditions
- Winning likelihood is not told, but the potential reward is given.



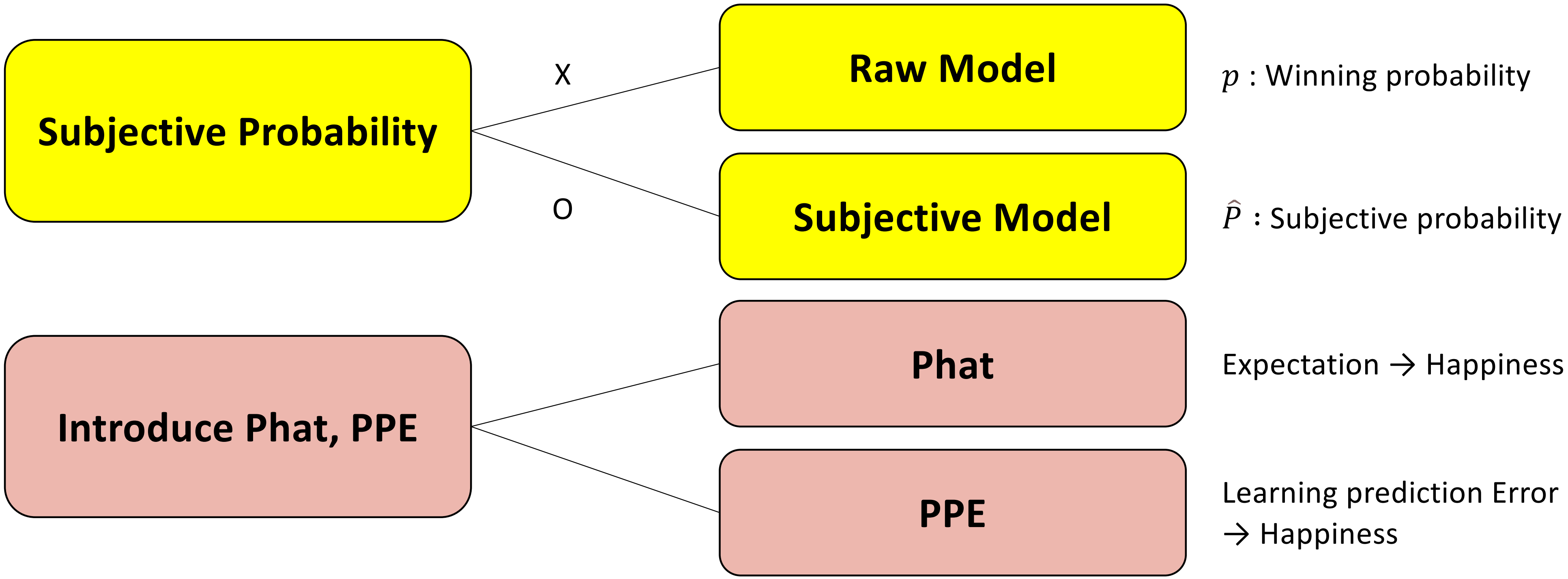
Data Description – Blain(2020)

- In total, 75 healthy participants
  - Used all participants as a single dataset
- Variables:
  - Probability and Value of each options (Winning prob = 0.8, 0.2)
  - Choice, Outcome, Happiness

Trial Num	Prob1	Prob2	Mag1	Mag2	Choice	Outcome	Happiness
1	0.2	0.8	20	40	1 (right)	40	79
2	0.2	0.8	10	60	1	60	
3	0.2	0.8	40	20	0 (left)	0	65

Adding Parameters

Consider subjectivity by adding parameters



Final Candidate Models

Original Model	Subjective Original	Phat + PPE	Subjective Mixed
- w_0 - w_{CR} - w_{EV} - w_{RPE} - γ : Decay rate	- w_0 - w_{CR} - w_{EV} - w_{RPE} - γ : Decay rate - α : Learning rate	- w_0 - w_P - w_{PPE} - γ : Decay rate - α : Learning rate	- w_0 - w_{CR} - w_{EV} - w_{RPE} - w_{PPE} - γ : Decay rate - α : Learning rate
- Parameter Estimation: MLE, Individual Bayesian, Hierarchical Bayesian - Model Comparison: LOO			

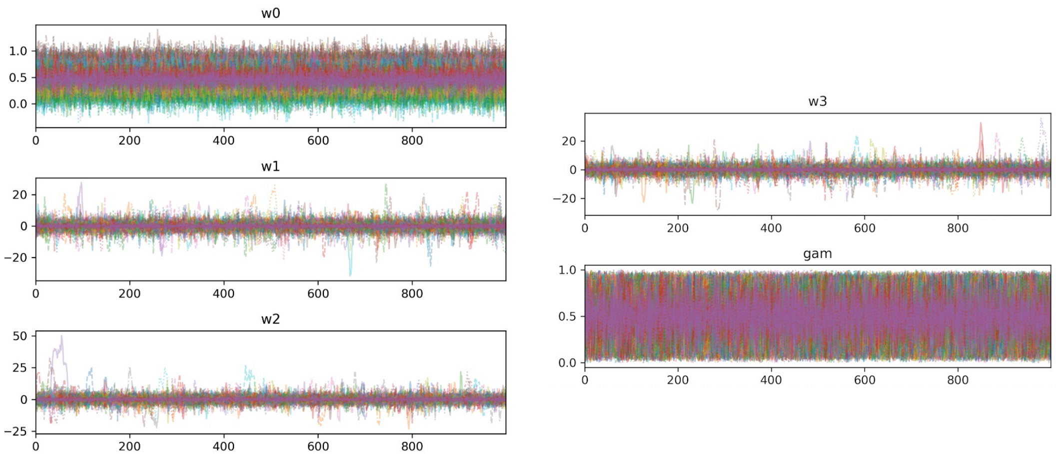
- $\mu_n, \sigma_n \sim Normal(0\,, 1)$
- $w_{n,pr} \sim Student\_t(3, 0\,, 1)$
- $w_{n,i} = \mu_n + \sigma_n \cdot n_{\,pr,i}$

- $\mu_\gamma \sim beta(2{,}2)$
- $\mu_\alpha \sim beta(2{,}2)$
- $\gamma \sim phi\_approx(\mu_\gamma + \sigma_\gamma * \gamma_{pr})$
- $\alpha \sim inv\_logit(\mu_\alpha + \sigma_\alpha * \alpha_{pr})$

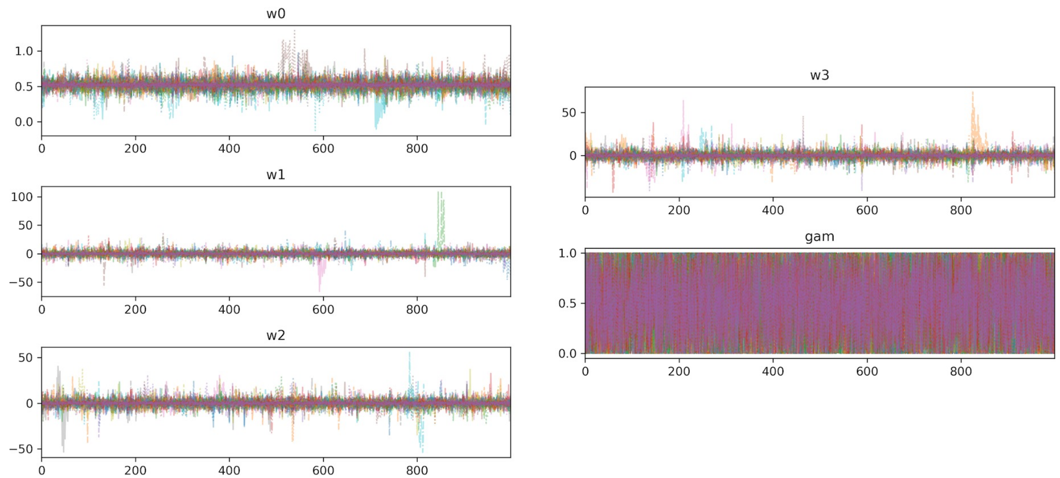
- μ_i= (weighted sum)
- $happiness_i = Normal(\mu_i, 1.0)$

Results: Original Model

Individual Bayesian(Rhat = 1), Hierarchcial Bayesian(Rhat = 1)



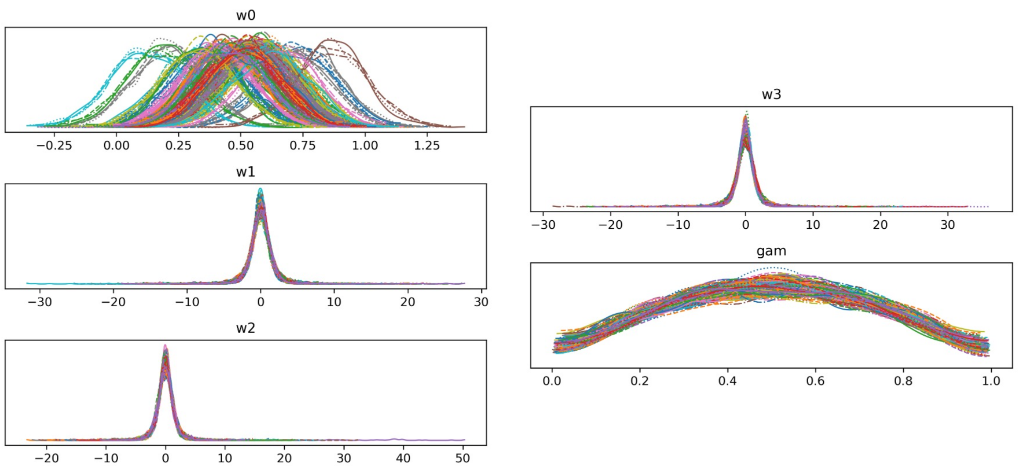
Individual Bayesian



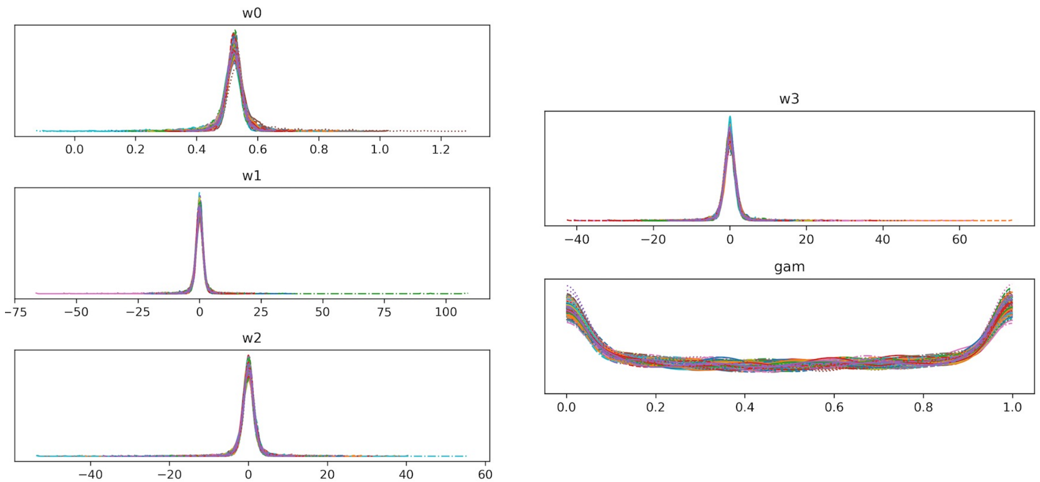
Hierarchical Bayesian

Results: Original Model

Posterior distributions of individual & Hierarchical estimations' parameters

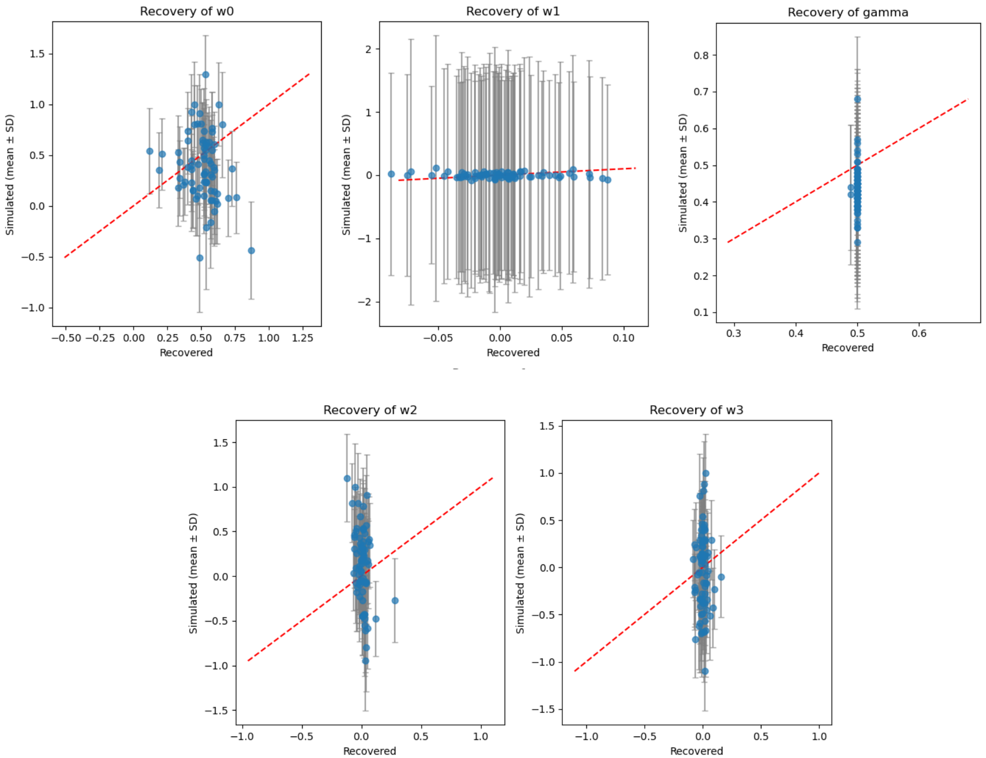


Individual Bayesian

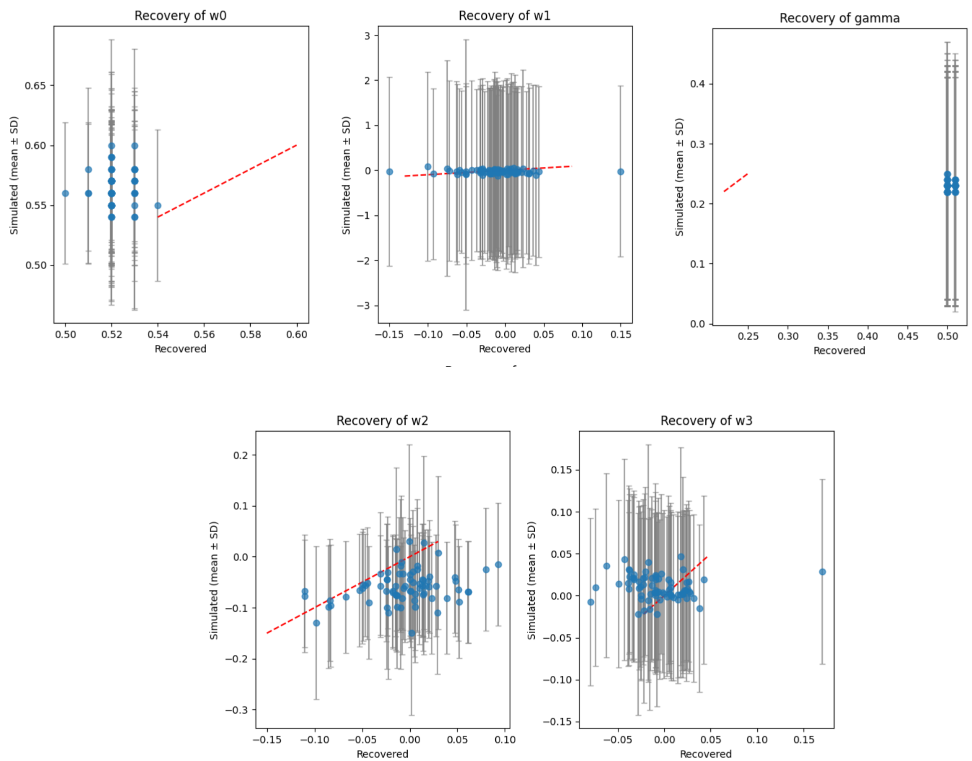


Hierarchical Bayesian

Results: Original Model – Parameter Recovery



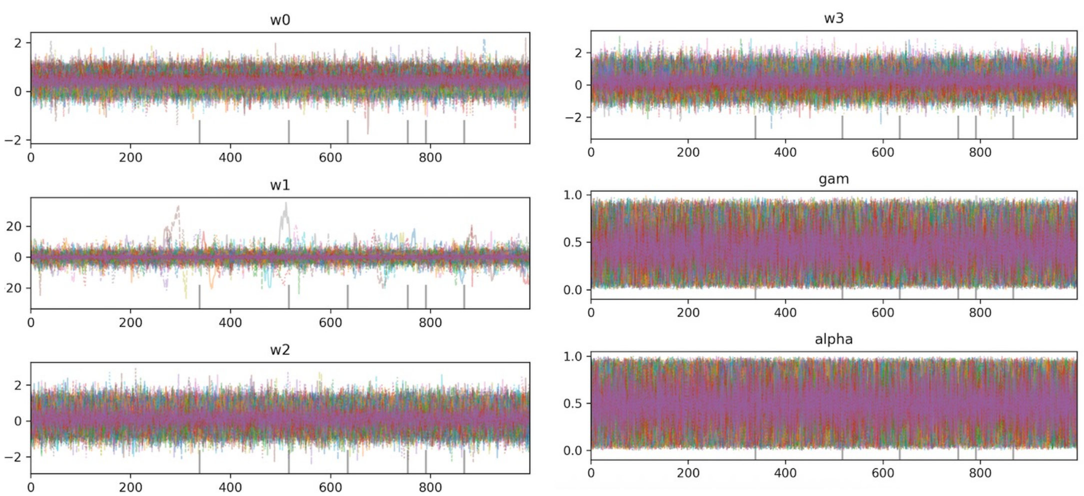
Individual Bayesian



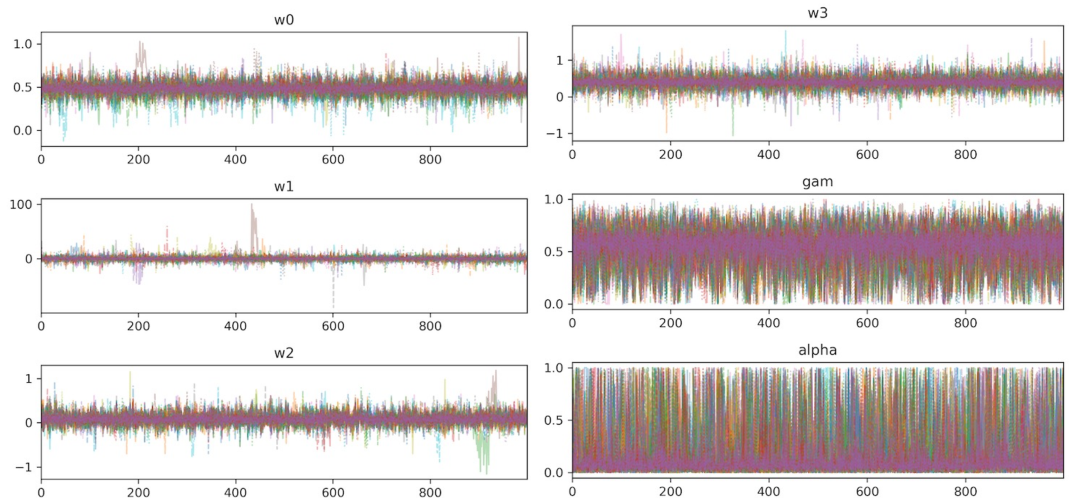
Hierarchical Bayesian

Results: Subjective Original Model

Individual Bayesian(Rhat = 1), Hierarchcial Bayesian(Rhat = 1)



Individual Bayesian

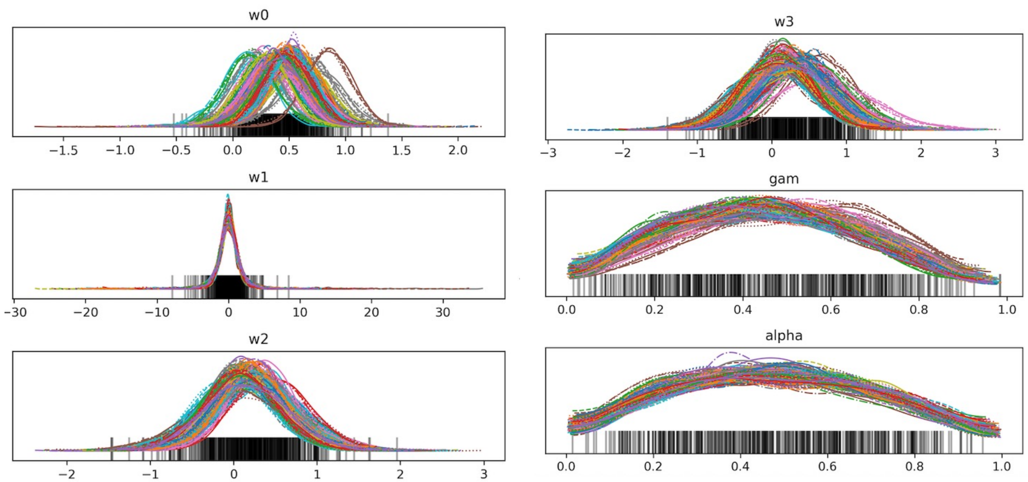


Hierarchical Bayesian

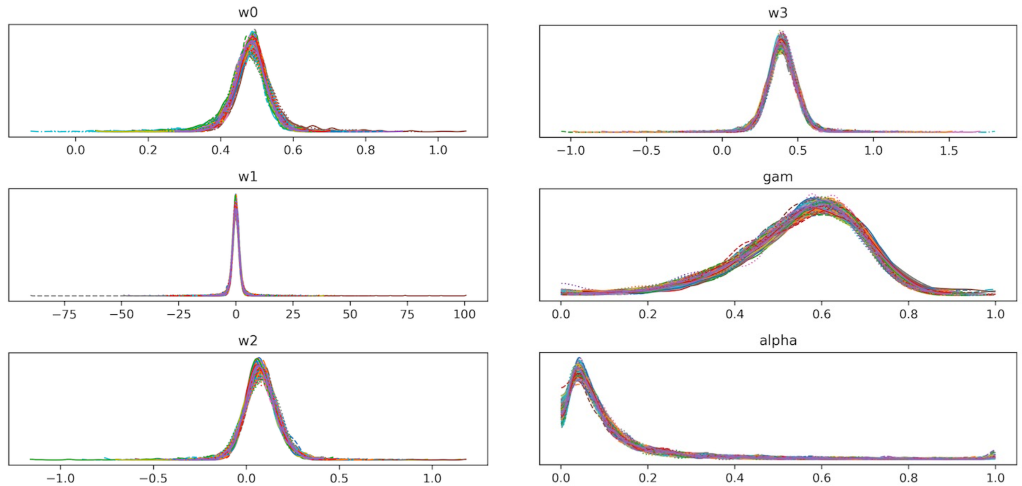
03. Results

Results: Subjective Original Model

Posterior distributions of individual parameters

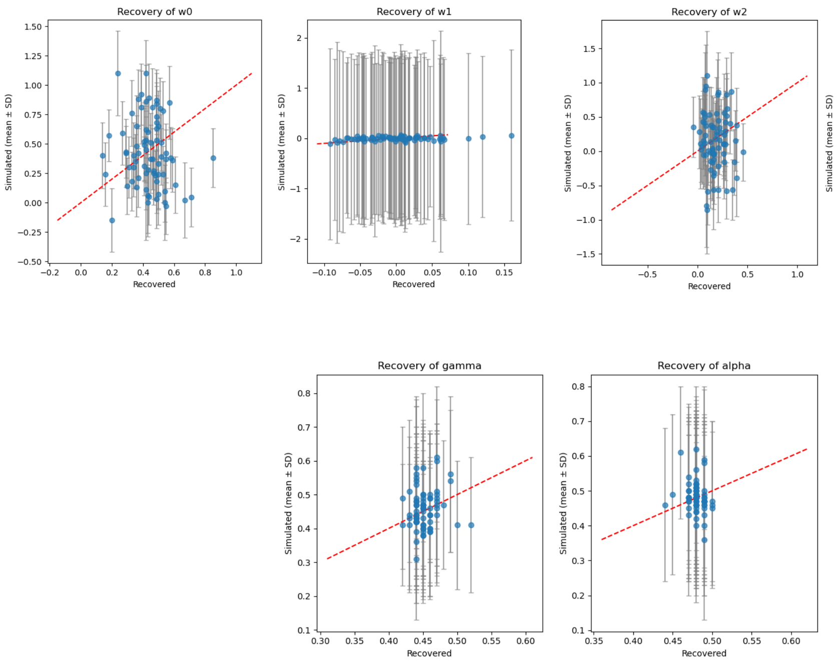


Individual Bayesian

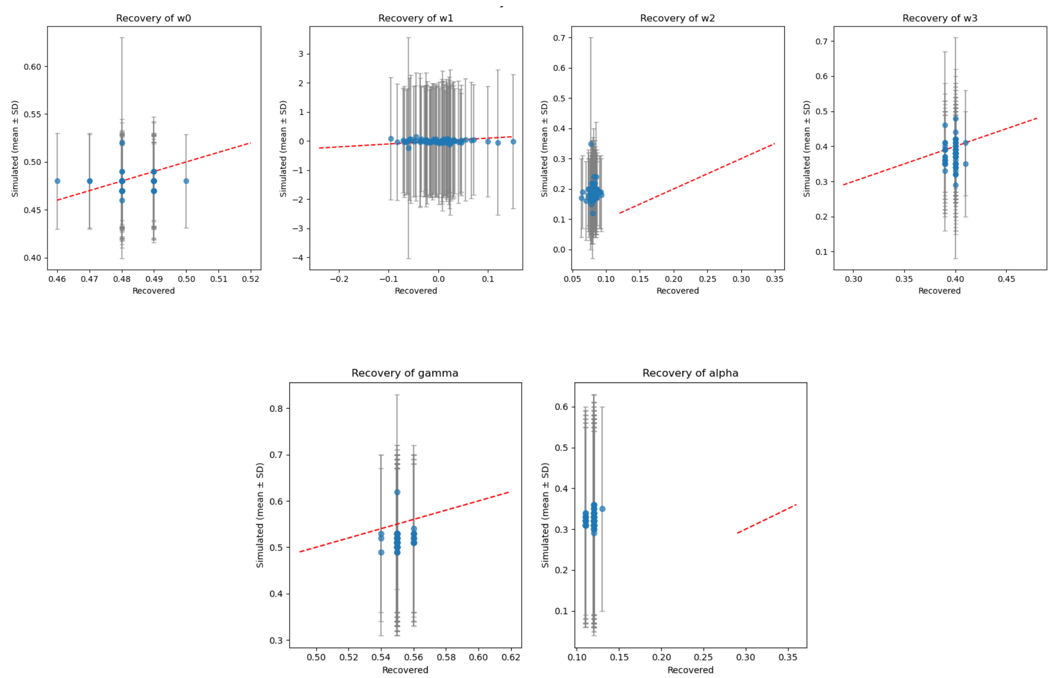


Hierarchical Bayesian

Results: Subjective Original Model – Parameter Recovery



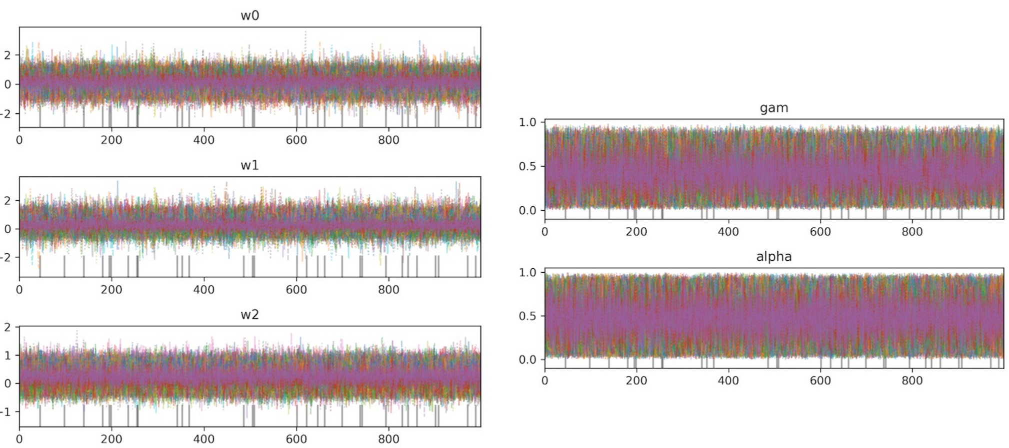
Individual Bayesian



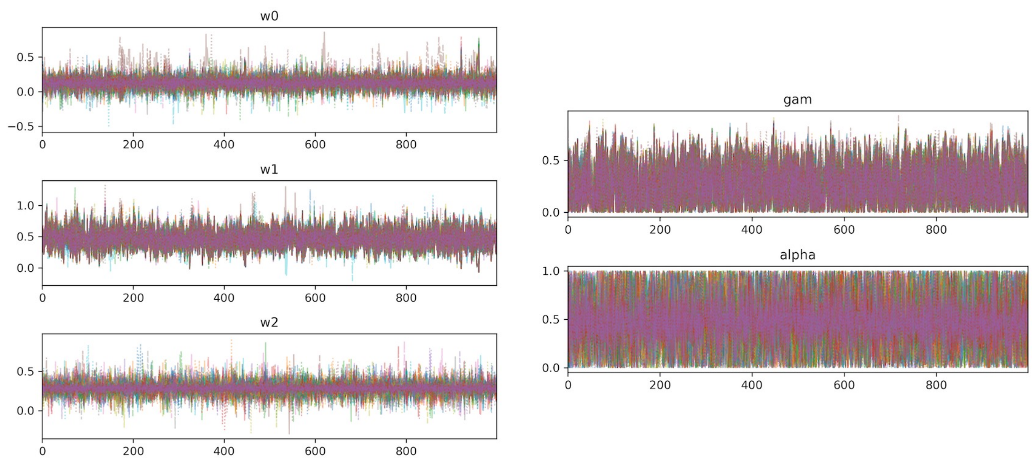
Hierarchical Bayesian

Results: Phat + PPE Model

Individual Bayesian(Rhat = 1), Hierarchcial Bayesian(Rhat = 1)



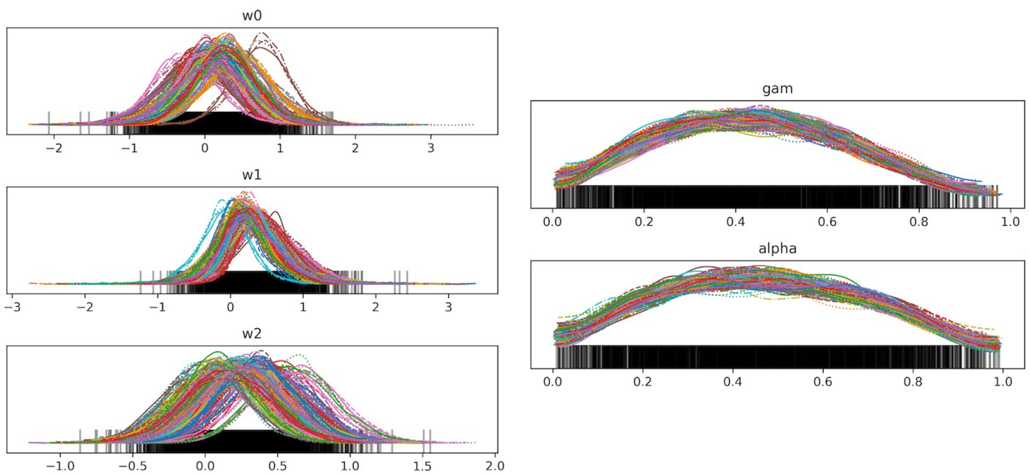
Individual Bayesian



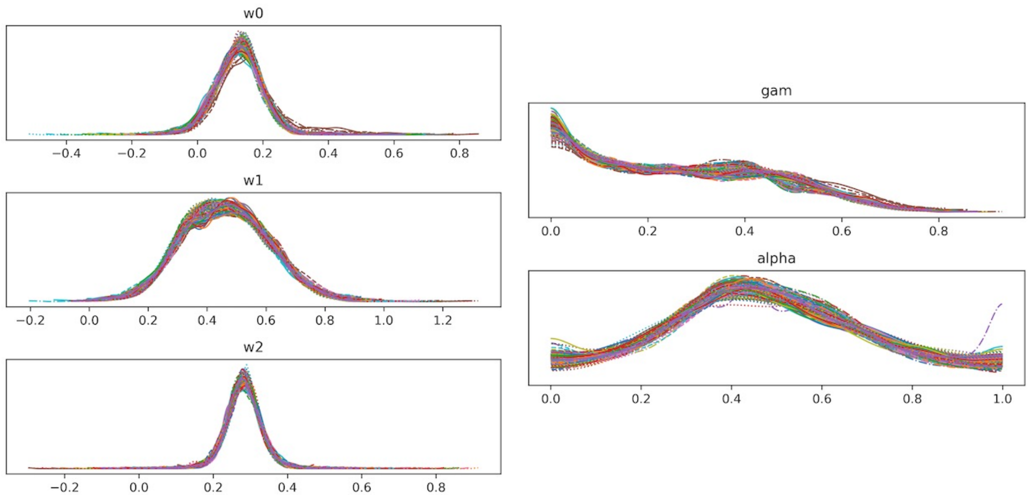
Hierarchical Bayesian

Results: Phat + PPE Model

Posterior distributions of individual parameters

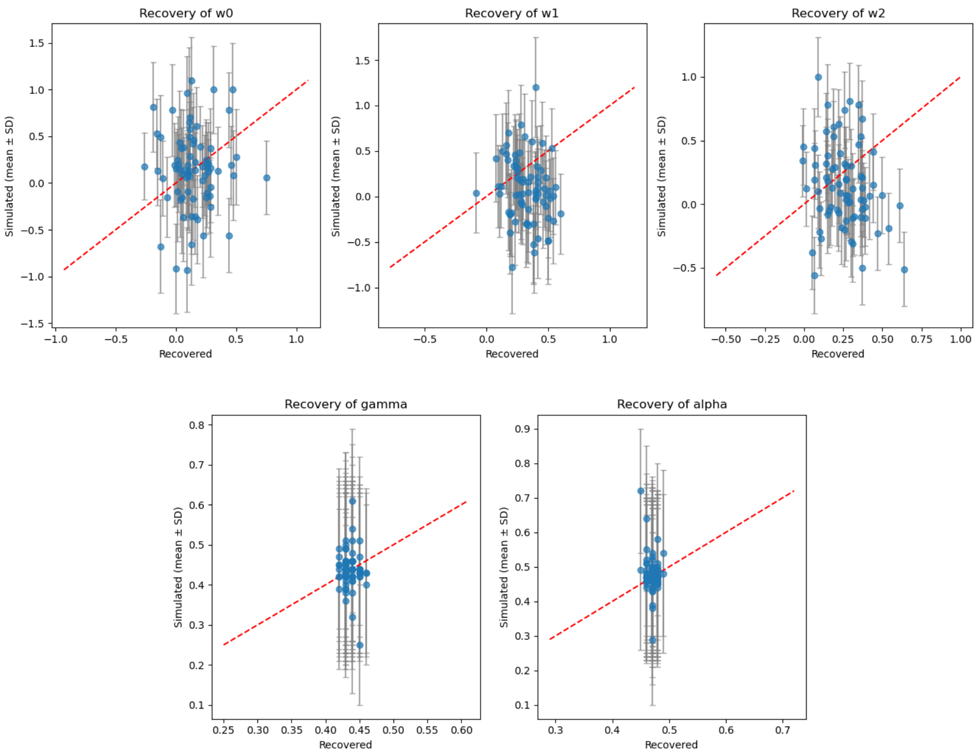


Individual Bayesian

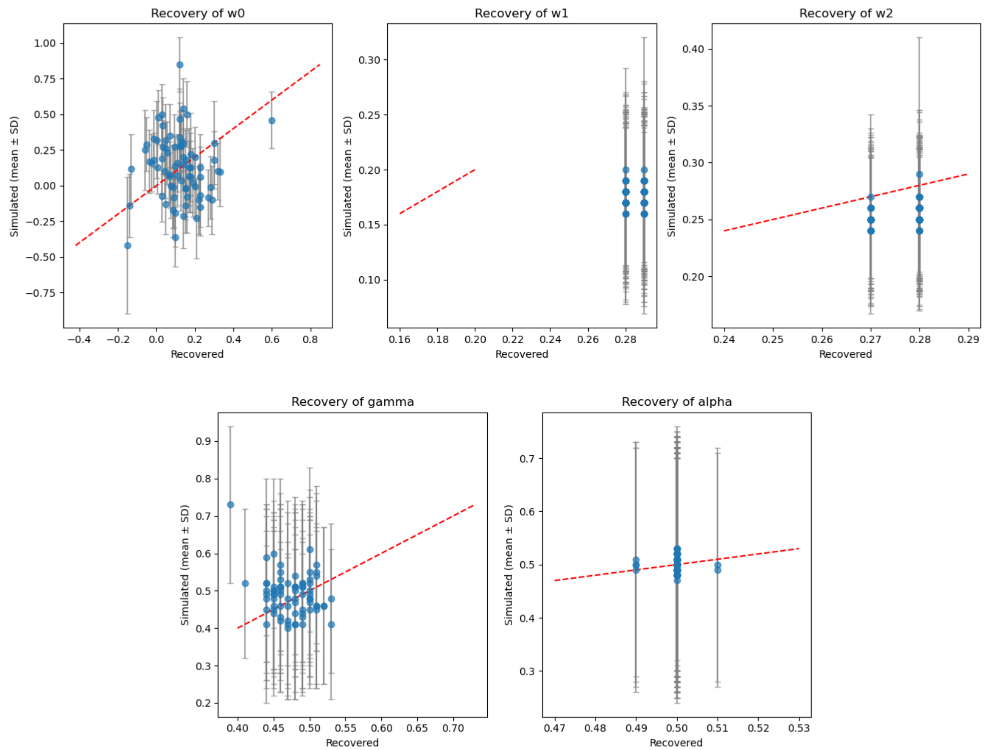


Hierarchical Bayesian

Results: Phat + PPE Model – Parameter Recovery



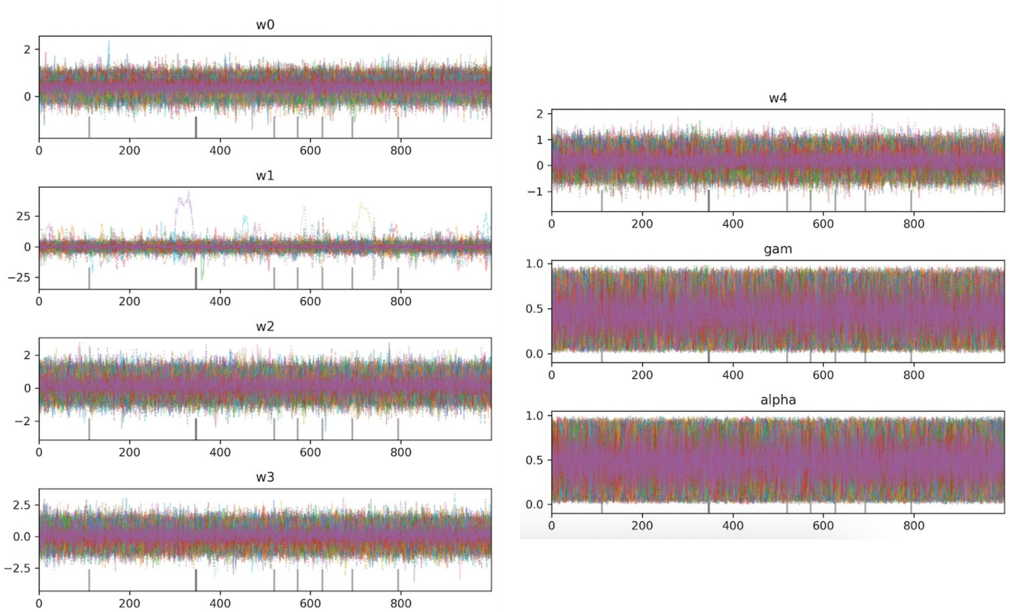
Individual Bayesian



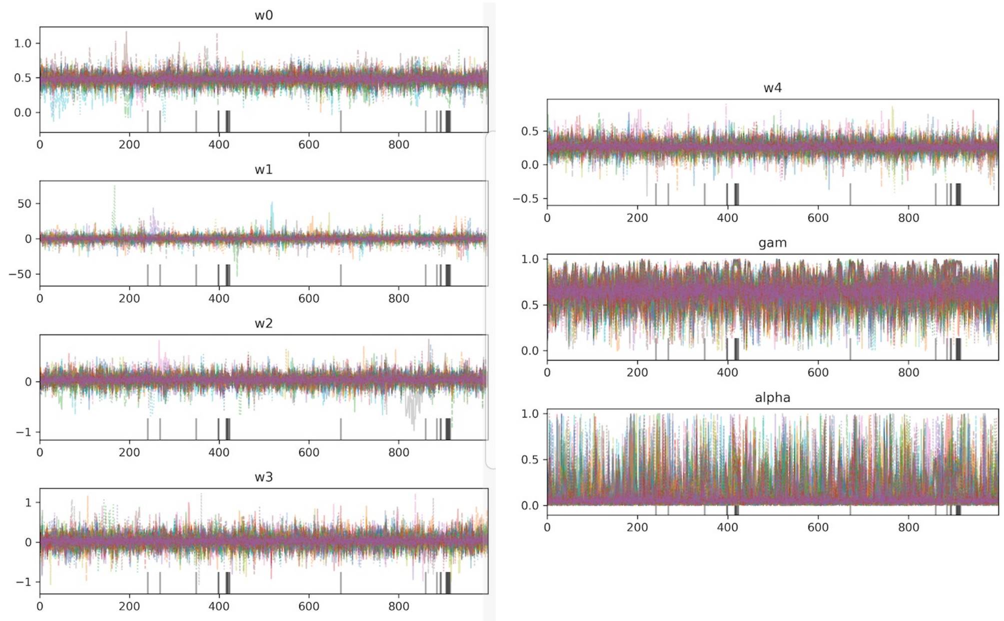
Hierarchical Bayesian

Results: Subjective Mixed Model

Individual Bayesian(Rhat = 1), Hierarchcial Bayesian(Rhat = 1)



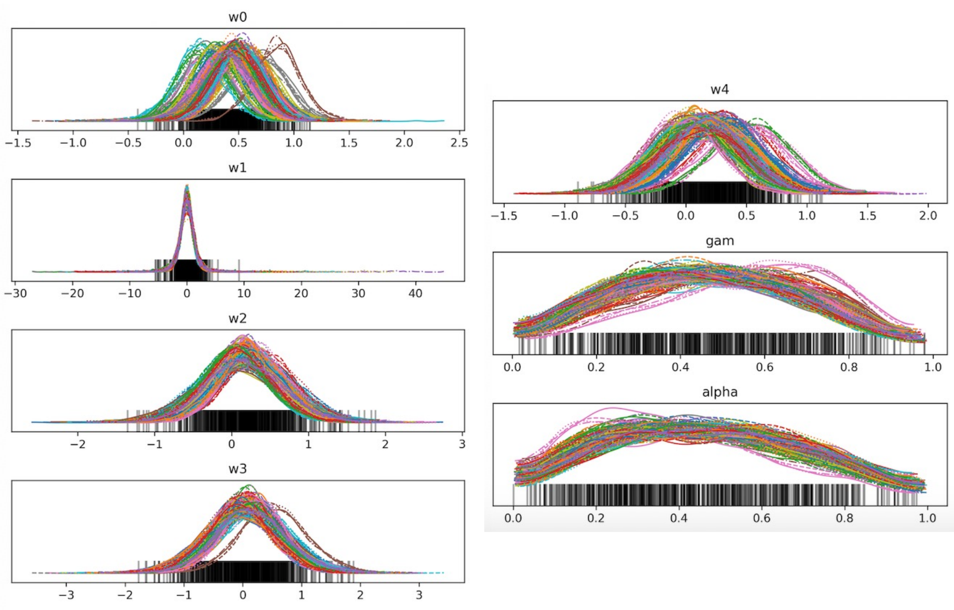
Individual Bayesian



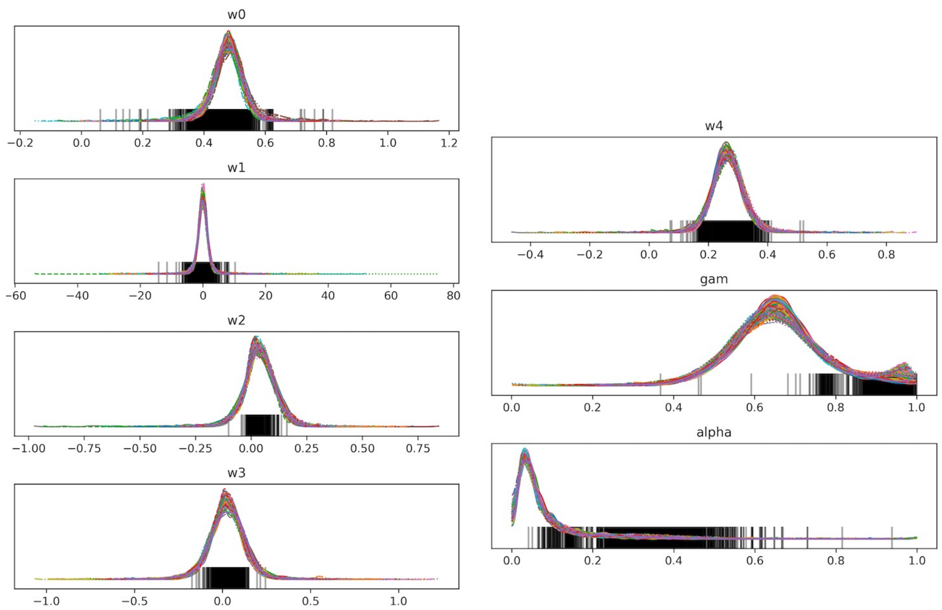
Hierarchical Bayesian

Results: Subjective Mixed Model

Posterior distributions of individual parameters



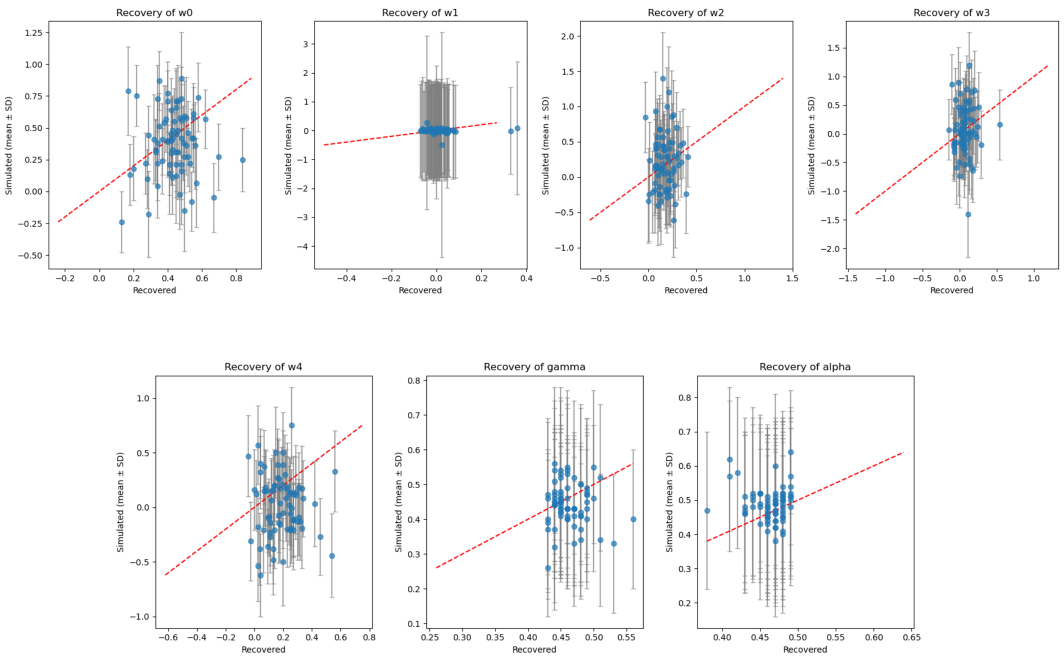
Individual Bayesian



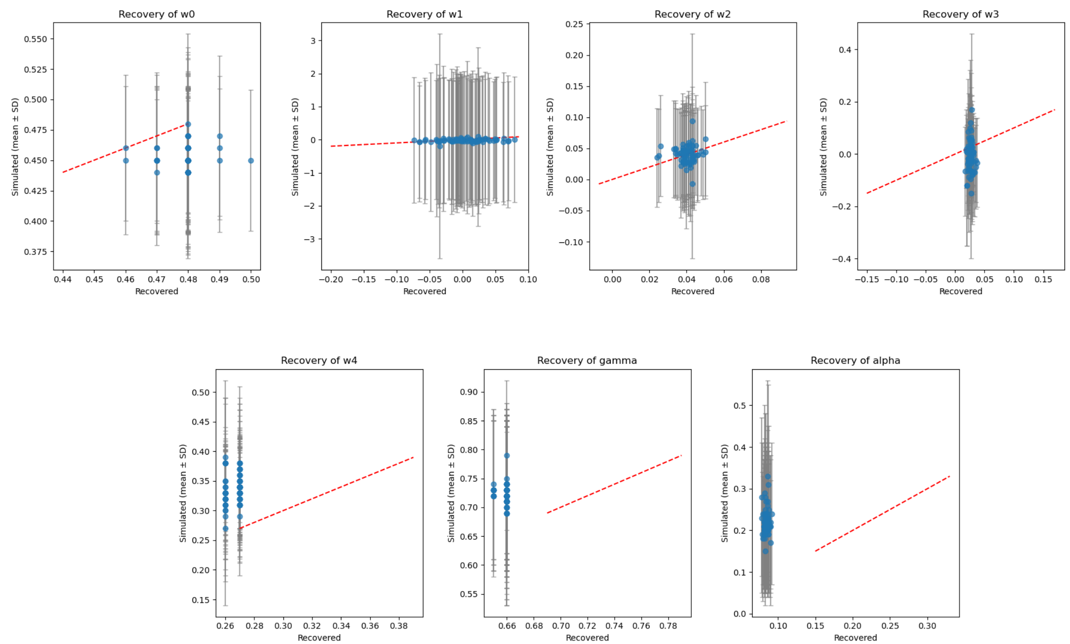
Hierarchical Bayesian

03. Results

Results: Subjective Mixed Model – Parameter Recovery



Individual Bayesian



Hierarchical Bayesian

Results: Model comparison & Parameters

- Model Comparison: LOOIC

LOOIC = Estimate(Standard Error)

Original – Individual : 3334.4 (2.73)	Original – Hierarchcial : 3319.5 (2.58)
Subjective Original – Individual : 3375.2 (2.71)	Subjective Original – Hierarchcial : 3299.8 (2.41)
Phat + PPE– Individual : 3331.0 (1.84)	Phat + PPE– Hierarchcial : 3271.6 (2.27)
Subjective Mixed – Individual : 3387.5 (2.46)	Subjective Mixed – Hierarchcial : 3273.6 (2.27)

- Each Parameter's effect on happiness

*Mean of coefficients from the top two HBA models by average coefficient value

	W_EV	**W_RPE**	**W_PPE**	**W_Phat**
1st (model)	0.08 (Sub)	0.396 (Sub)	0.28 (PhatPPE)	0.46 (PhatPPE)
2nd (model)	0.04 (Mixed)	0.026 (mixed)	0.27 (mixed)	-

Effect of Depression on Coefficients

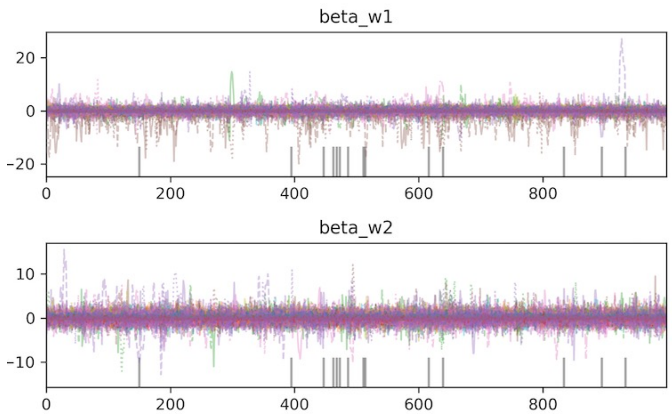
Separate hyperparameters for Depression group

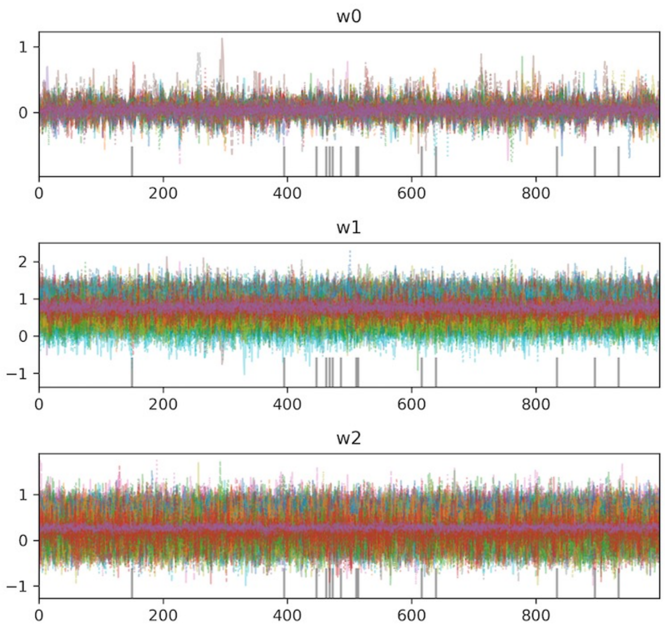
- Based on the PhatPPE Model, which showed the lowest LOO value.
  - Imbalance between the number of each depression group
    - Minimal: 55, Mild: 9, Moderate: 9, Severe: 2
    - Setting different hyperparameter for HC and Depression group was infeasible.
  - Set slopes for each parameter weights in PhatPPE Model
    - $w_{PPE_{[i]}} = mu_{PPE} + \beta_{PPE} * BDI_{[i]}$
    - β_{PPE} : Can regularized BDI value [-1, 1] explain individual differences?
      - $\beta_{PPE} > 0$: Individuals with high depression are more sensitive to such variables
      - $\beta_{PPE} < 0$: Individuals with high depression are less sensitive to such variables

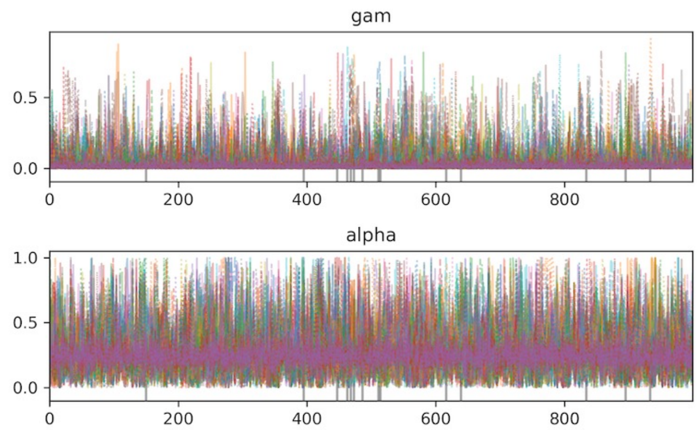
03. Results

Result: Depression Model

Convergence (Rhat = 1)

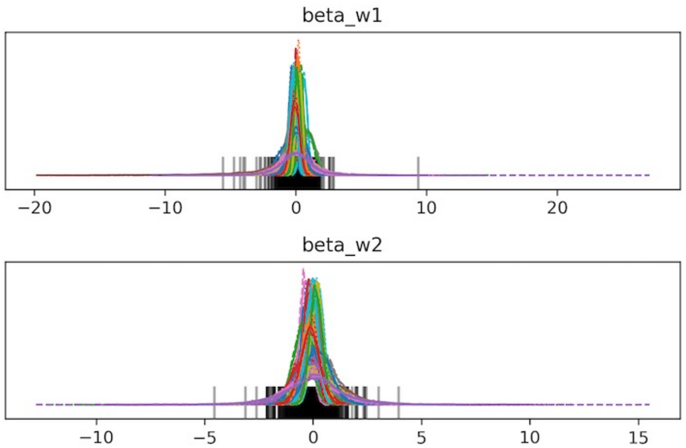




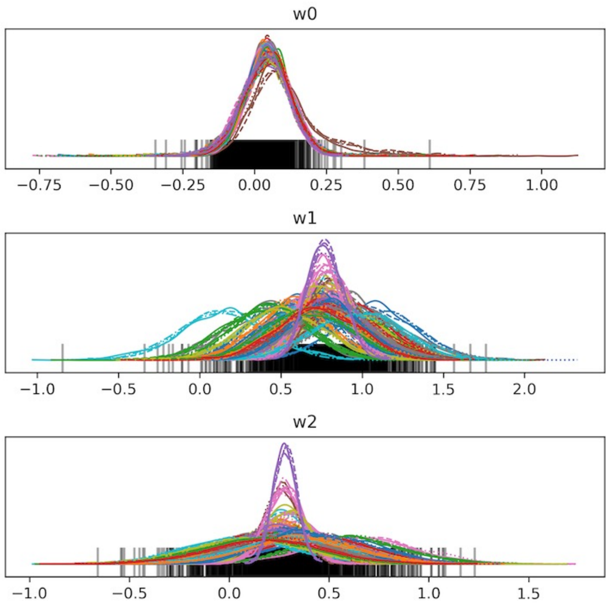


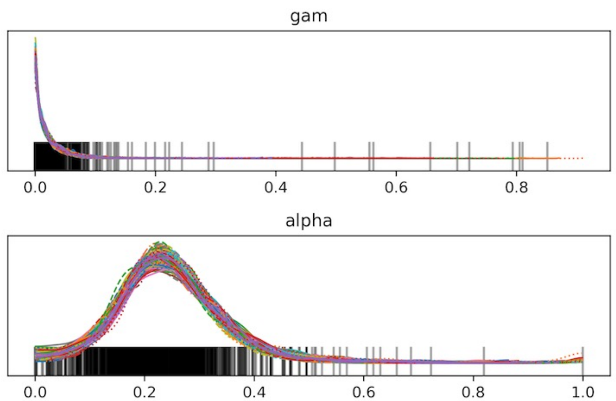
Result: Depression Model

Posterior distributions of individual parameters



β_{Phat} : -0.002 [-0.89, -0.86]
β_{PPE} : -0.001 [-0.96, 0.93]





04. Conclusions

Discussions

- Hierarchical Bayesian approaches showed better estimation than the others.
  - For every model, HBA models showed lower LOO value, with successful parameter recovery
- New models estimates happiness better than the original model.
  - Models that considers subjective probability showed better results than the original model with absolute winning probability
  - Phat + PPE model showed the lowest LOO value, followed by Subjective-Mixed Model.
- Task related prediction error predicts happiness better than reward prediction error.
  - Phat and PPE showed significant values within including models.
  - Even if RPE showed a significant value in Subjective-Original Model, its explainability diminished with introduction of PPE
- Difference between depression group and healthy control group was not significant.
  - Means of both β_{Phat} and β_{PPE} were near zero.

Limitations & Further Research

- Shrinkage
  - Shrinkage: Most of the parameter values in hierarchical Bayesian model shrink to the mean of each parameter.
  - Dataset: Given regularized reward values and happiness to a range of [-1, 1], multiplying such values with probability (0, 1) led to shrinkage of estimation
  - Due to shrinkage, investigating the impact of depression on each parameter weights was infeasible (Limited individual differences)
- Further Research
  - Data Modification: Increase scale of each variable to [0, 80] and [0, 100] to alleviate shrinkage problem.
  - Data Acquisition: Get enough data for depression group, and divide participants into two groups with separate hyperparameters for Hierarchical Bayesian Models

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