Portfolio 2 text

Part 1

Q1 - Simulate data to setup the analysis and gain insight on the structure of the problem. Simulate one dataset of 100 studies, (n of participants should follow a normal distribution with mean of 20, sd of 10, but no fewer than 10 participants), with a mean effect size of 0.4, average deviation by study of .4 and measurement error of .8. The data you get should have one row per study with an effect size, mean and standard error.

Build a proper bayesian model to analyze the simulated data, then simulate publication bias, (only some of the studies you simulate are likely to be published, which?), the effect of publication bias on your estimates, (re-run the model on published studies, assess the difference), and discuss what this implies for your model.

Remember to use at least one plot to visualize your results.

BONUS question: do a power/precision analysis: w this kind of sample sizes (participants) how many studies would you need to acquire good precision (e.g. .1 sd in the pop level estimate)

To begin with, we simulate a dataset of effect sizes for 100 studies. The means of these studies are drawn from a normal distribution with a mean of 0.4 (mean population level effect size) and a standard deviation of 0.4 (average deviation by study). For all studies, we simulate a number of participants. The number of participants is drawn from a normal distribution with a mean of 20 and a standard deviation of 10. All participants are then given a simulated measurement value drawn from a normal distribution with the study mean effect size as the mean and a standard deviation of 0.8 (measurement error). The hierarchical structure of the simulated data is visualised in Figure 1.

Parameter	Name in code	Value
Mean pop. level effect size	effect_mean	0.4
Average deviation by study	effect_sd	0.4
Measurement error	error_sigma	0.8

The estimated effect size and variability is then calculated for each simulated study. This is the data used for the simulated meta analysis (as normal meta analyses do not have access participant level effects).

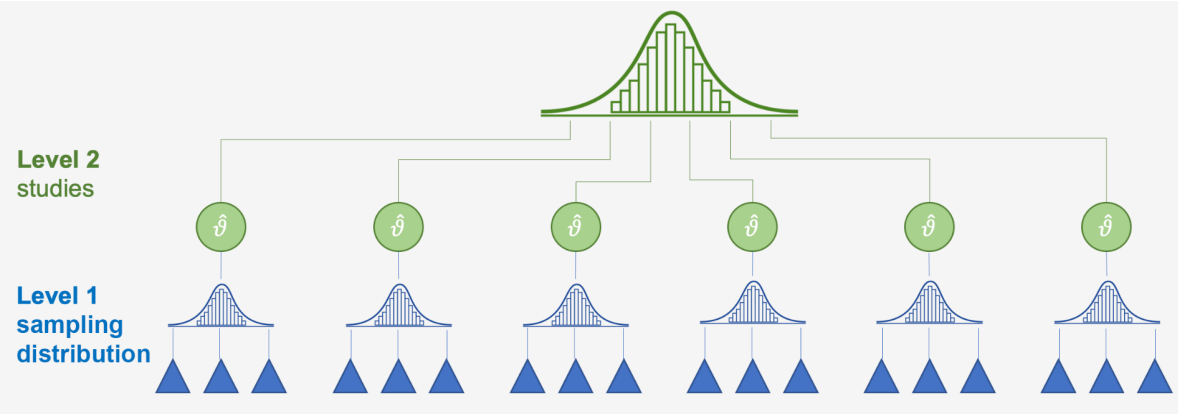

Figure 1. Hierarchical structure of the simulated data (blue)

Subsequently, we set our formula and define our priors within a plausible and somewhat sceptic range. Specifically, the formula is set to: *est_effectsize|se(est_se) ~ 1 + (1|study),* (the effect size is a distribution with a mean and a sd, varying by study) and our priors are specified for intercept and sd, both centred at 0 with a standard deviation of 0.3.

Then we run a model on our priors to inspect how well our prior specifications generate appropriate values.

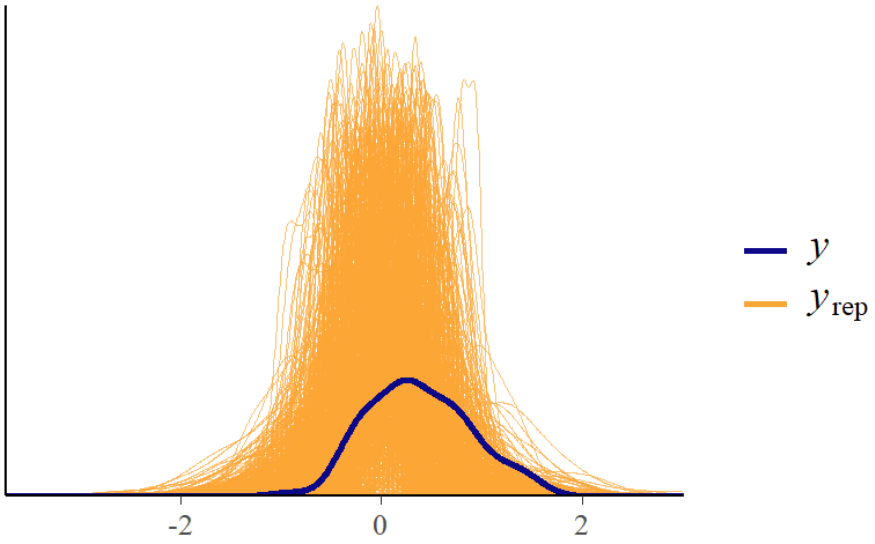

Figure 2. Prior predictive check

The predictions appear to have a slightly larger range than the (simulated) data. However, the vast majority are within the wanted range of the weakly informed priors that we set.

We fit the model to the simulated data, and following we conduct posterior predictive checks to see if our model has captured the data.

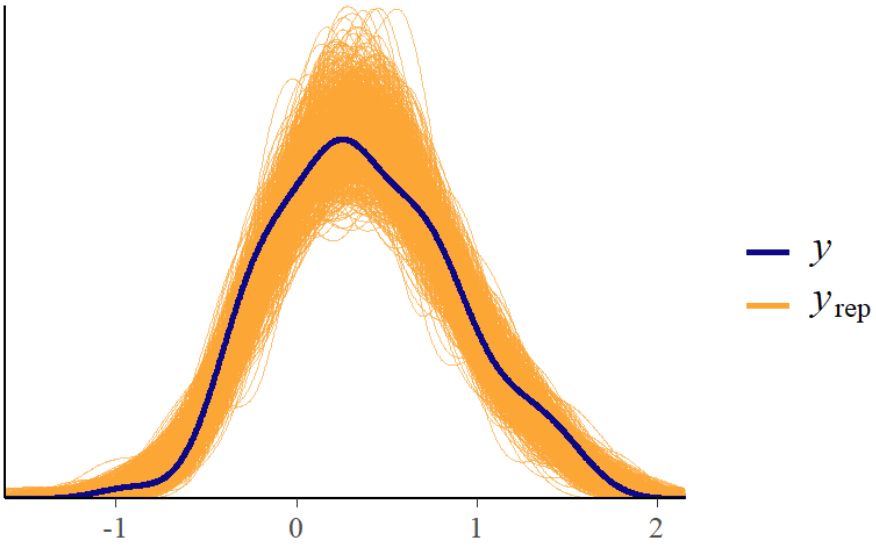

Figure 3. Posterior predictive check

The plot indicates that our model captures the general distribution of our data. No systematic differences are observable.

Finally, we plot prior-posterior update checks with lines to indicate the true mean effect size (i.e. 0.4)

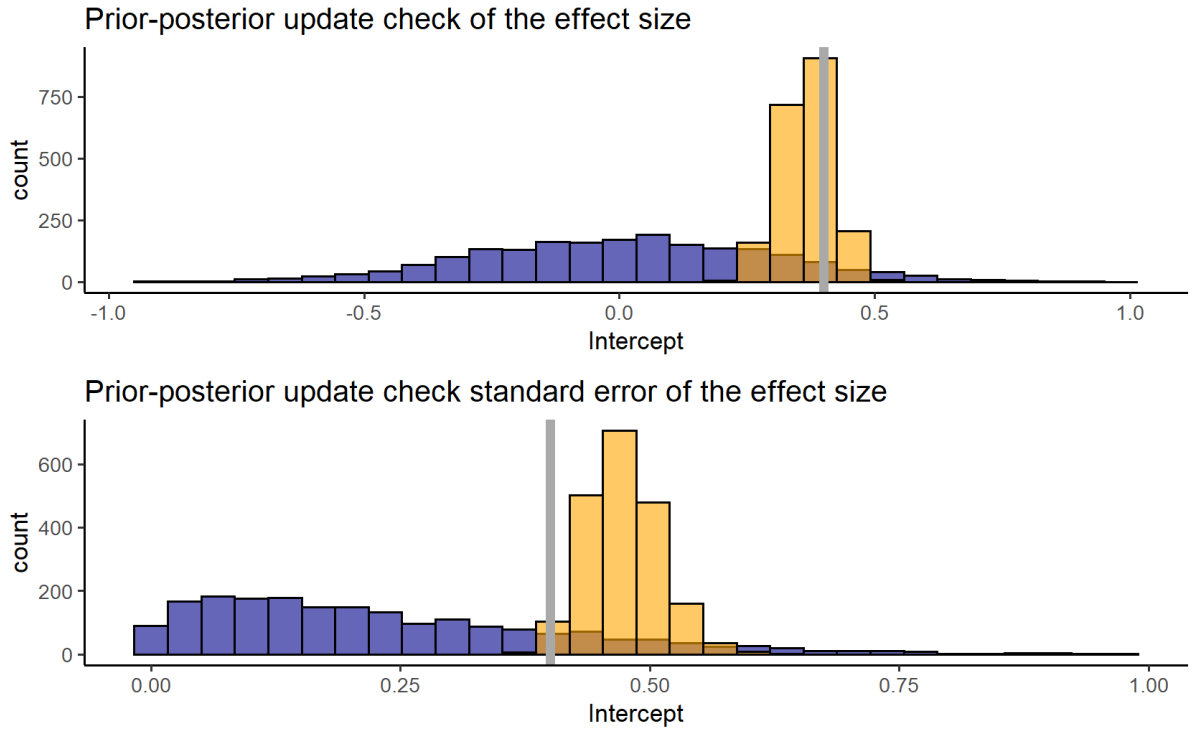

Figure 4. Prior-posterior update checks

The first check suggests that our posterior prediction of the effect size lies within the set prior. Moreover, the posterior distribution is narrower than the prior, which indicates that our model has learned from the data and gained some confidence in its predictions.
In the second check - standard error of the effect size - we can see that our posterior is within the upper bounds of the prior. Additionally, the posterior distribution is narrower than the prior one, which suggests, yet again, that the model has learned from the data.

Lastly, we compare the estimate with the true value. The model estimated the effect size to be 0.37, while the standard error of effect size by study comes out to be 0.47. Both are close to their true value counterparts, which suggests that our model has performed well.

Publication bias

Then we want to introduce publication bias into our model, in order to be able to assess the influence that publication bias might have on a real meta analysis. In the simulation, studies that found to have an effect size that lies more than 2 standard errors away from 0 (resembling a 95% significance level) are assigned a 90% chance of getting published,

whereas the studies that do not have effect sizes that are significantly different than 0 only have a 10% chance of getting published. By doing this, our estimates change. The standard error of effect size by study now comes out to be 0.43, and the effect size drastically changes and becomes 0.61. Thus, it seems that the publication bias skewes the estimates. Moreover, a new posterior predictive check displays a change compared to Figure 3:

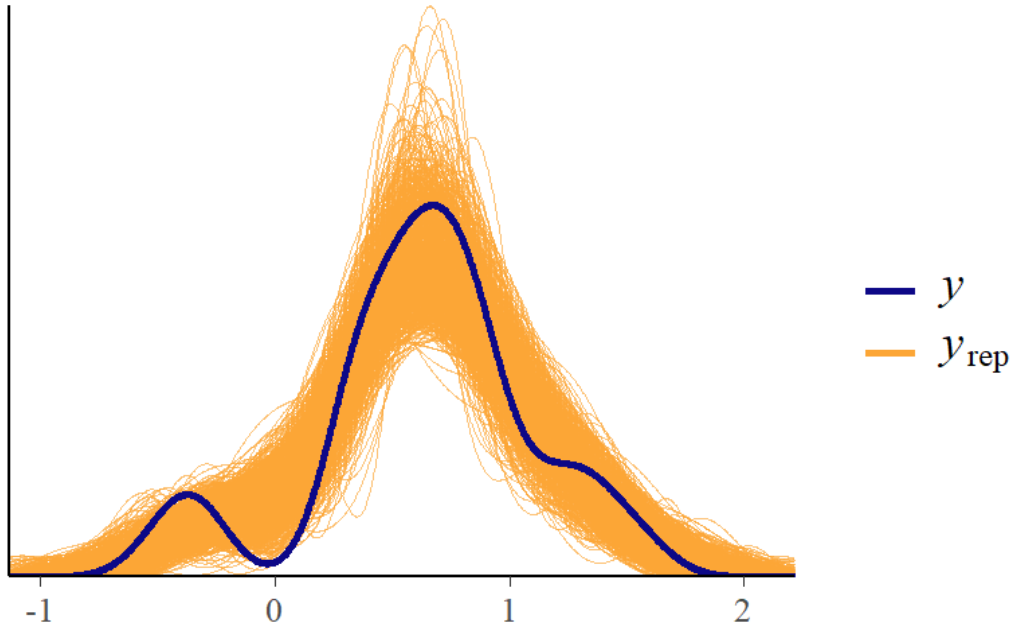

Figure 5. Posterior predictive check w. publication bias

The check shows the effect of publication bias, as such, there are almost no studies around zero.

Part 2

Q2 - What is the current evidence for distinctive vocal patterns in schizophrenia?

Use the data from Parola et al (2020) - https://www.dropbox.com/s/0l9ur0gaabr80a8/Matrix_MetaAnalysis_Diagnosis_updated290719.xlsx?dl=0 - focusing on pitch variability (PITCH_F0SD). Describe the data available (studies, participants). Using the model from question 1 analyse the data, visualise and report the findings: population level effect size, how well studies reflect it, influential studies, publication bias.

BONUS question: assess the effect of task on the estimates (model comparison with baseline model)

The data from Parola et al. (2020) contains 50 studies about vocal patterns in people with schizophrenia.The data is used to perform a meta analysis on their findings.
7 out of the 50 studies are duplicates, as a result of them performing multiple investigations. However, they remain compatible with the inclusion criteria. Only 15 studies contain effect sizes of pitch variability, which are the ones that will be used in our analysis. Methods of speech production vary or are unspecified. The studyID's are renamed and multivariate investigations are considered as individual studies. Pitch variability effect sizes were stated in different scales, however this is disregarded for the purpose of the assignment, and Cohen's d effect size calculations are used to homogenise the effect sizes across the scales.

The sample sizes of the 15 studies are shown below - both total sample sizes and by group:

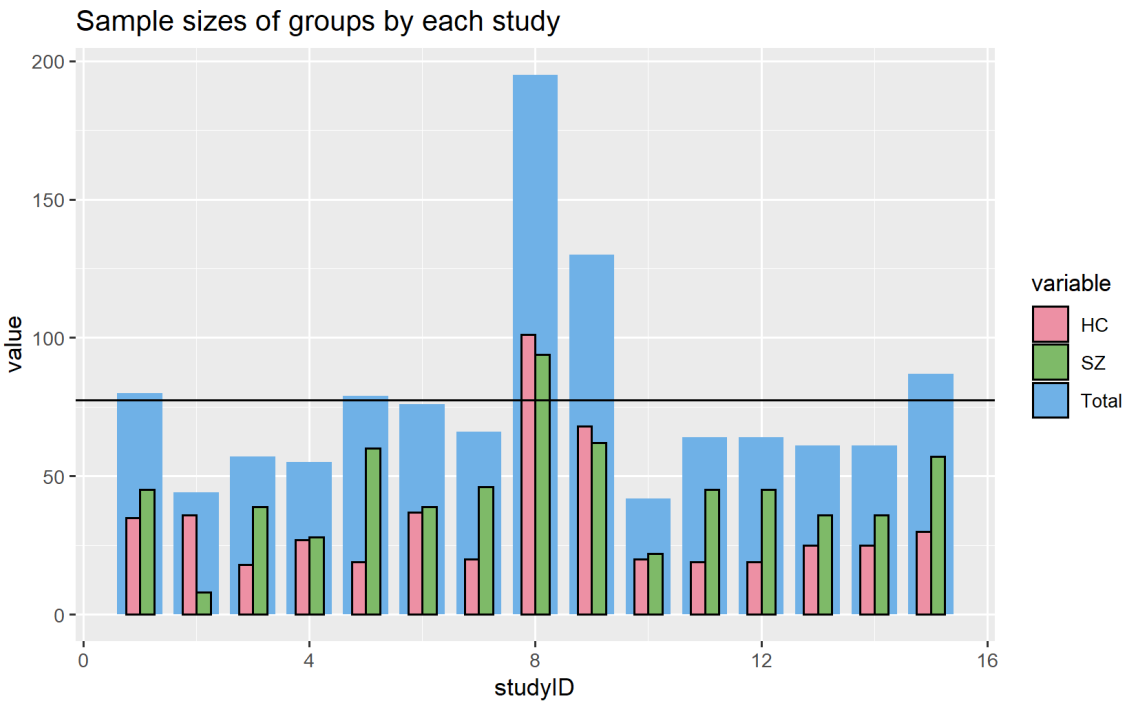

Figure 6. Plot of sample sizes across groups, HC - Healthy Controls, SZ - Schizophrenic participants. The vertical line represents the mean of total sample sizes (≈ 77 participants).

As one would expect, there is an uneven distribution of total sample sizes between the two groups, mostly with a slight overweight of SZ-participants (*mean_SZ ≈ 44, mean_HC ≈ 33)*.

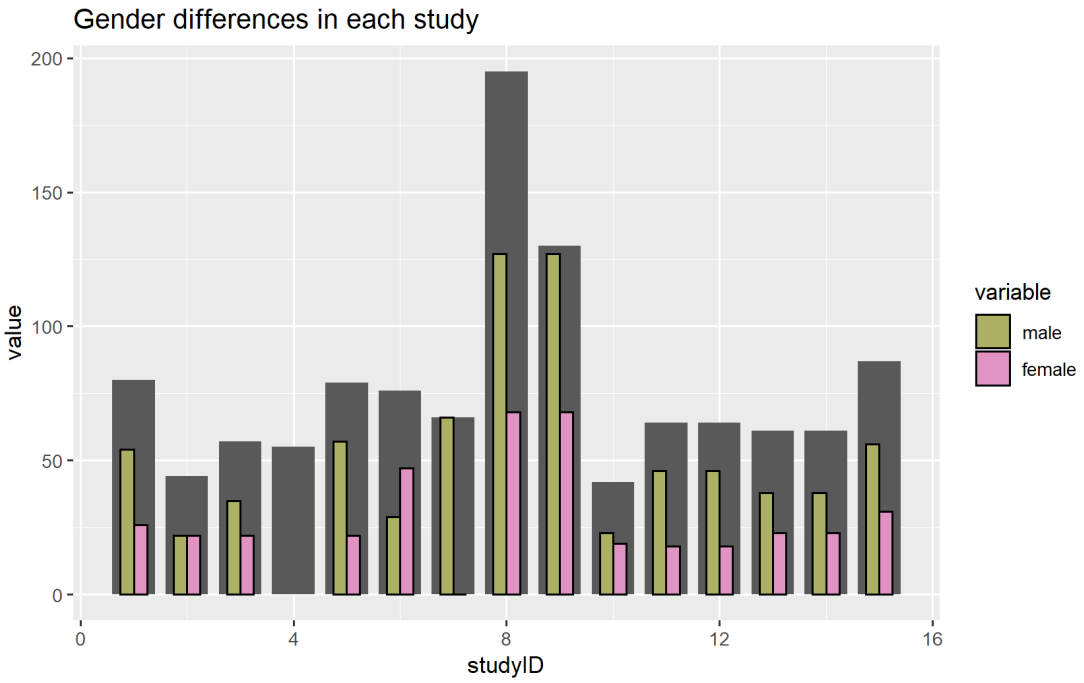

Figure 7. Plot of gender distributions across studies

The differences in gender across studies show that most studies had more male participants than female (*mean_female ≈ 29, mean_male ≈ 54)*. When comparing the means of gender within the SZ-group (*male_SZ ≈ 35, female_SZ ≈ 13)*, indications of higher prevalence of schizophrenia in men could potentially explain the gender differences across the studies. Study 4 had no registration of gender of their participants. Study 8 and study 9 are one multivariate study; they reported different sample sizes by group, but same sample sizes of gender, which is why the distribution of study 9 is unbalanced.

Fitting the model to the actual data, we see that the estimates of the model changes. The model estimates that the population level effect would be 0.14 with a standard error of 0.92. This is quite a big variability, which suggests that the studies show a diverse set of effects. In Figure 8 we see that the prior-posterior update check of the effect size shows that the model hasn't learned a lot from the data since its posterior is not much narrower than its prior. The prior posterior update check of the standard error of the effect size seems to be pushing the boundaries of the priors substantially.

Figure 8. Prior-posterior update checks

Looking at the posterior predictive check of the model fitted to the real data (Figure 9) from the meta analysis, we notice that the distribution quite closely resembles the structure of the simulated data including publication bias (Figure 10). This could indicate that the studies used in the meta-analysis might be under influence of publication bias. Therefore we should

be sceptical when using our estimated population level effect size to make inferences about pitch variability in schizophrenia.

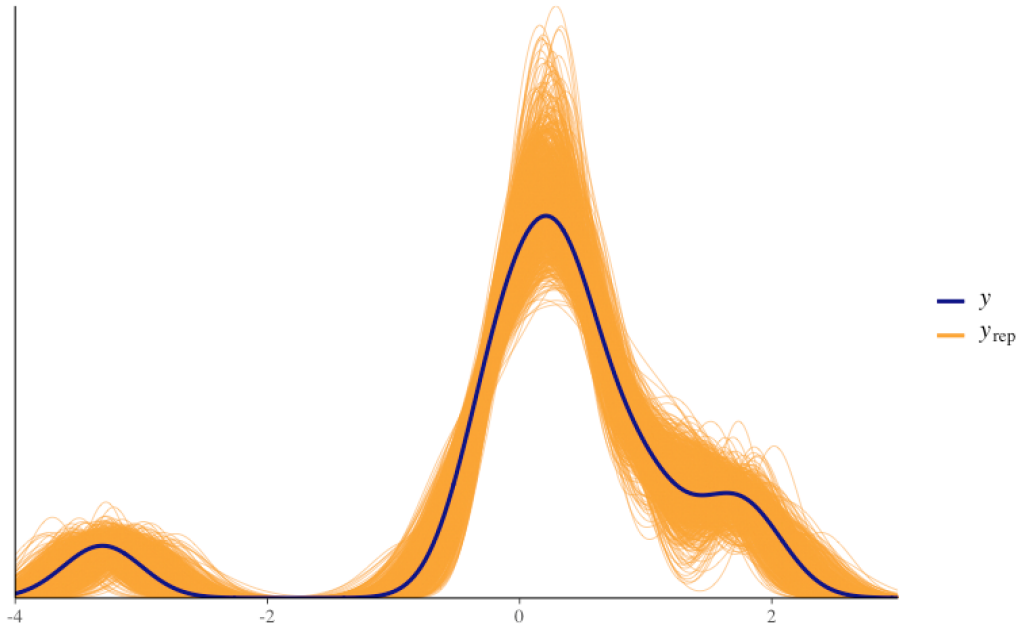

Figure 9. Posterior predictive check of the model fitted to the real data

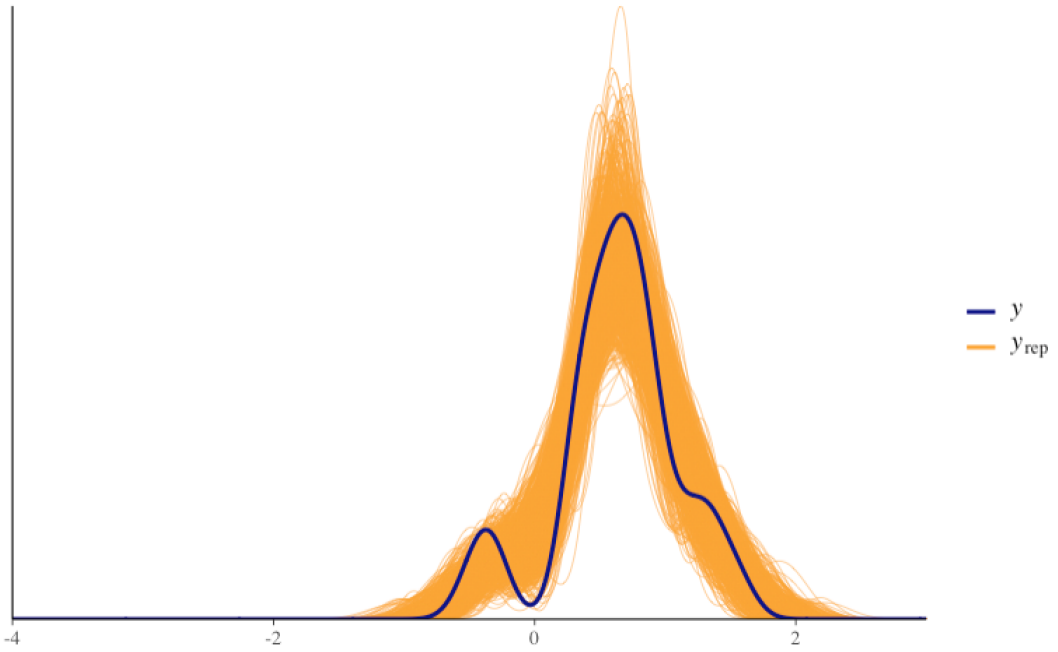

Figure 10. Posterior predictive check of the model fitted to simulated data with publication bias

ifelse(pass==T, print("We happy :)"), print("😭")) #🙏🙏