

Social priming in speech perception: revisiting Kangaroo/Kiwi priming in New Zealand English

Supplementary materials - R code for models and plots

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21 March, 2022

Document outline

This document provides the code used in the analyses of the Hurring, Hay, Drager, Podlubny, Manhire, and Ellis (2022) manuscript, submitted to Brain Sciences. It contains the various analysis steps reported in the paper. Access to the data files are found in the same folder as this file. As described in the manuscript, the data was collected from two online lexical decision tasks, and extracted from Google's Firebase console.

Install and load libraries

The following libraries need to be installed and loaded into the Rmd to run the code below.

```
library(tidyverse) #various functions

## -- Attaching packages ----- tidyverse
1.3.1 --

## v ggplot2 3.3.3      v purrr  0.3.4
## v tibble  3.1.1      v dplyr  1.0.6
## v tidyr   1.1.3      v stringr 1.4.0
## v readr   1.4.0      v forcats 0.5.1

## -- Conflicts -----
tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()

library(DT) #
library(effects) #plots models

## Loading required package: carData

## lattice theme set by effectsTheme()
## See ?effectsTheme for details.

library(lme4) #runs linear regression models
```

```

## Loading required package: Matrix

##
## Attaching package: 'Matrix'

## The following objects are masked from 'package:tidyr':
##
##     expand, pack, unpack

library(rjson) #reads JSON files
library(standardize) #

##
## *****
##           Loading standardize package version 0.2.2
##           Call standardize.news() to see new features/changes
## *****

library(rms) #

## Loading required package: Hmisc
## Loading required package: lattice
## Loading required package: survival
## Loading required package: Formula

##
## Attaching package: 'Hmisc'

## The following objects are masked from 'package:dplyr':
##
##     src, summarize

## The following objects are masked from 'package:base':
##
##     format.pval, units

## Loading required package: SparseM

##
## Attaching package: 'SparseM'

## The following object is masked from 'package:base':
##
##     backsolve

library(sjPlot) #plots

## Registered S3 methods overwritten by 'parameters':
##   method                                from
## as.double.parameters_kurtosis          datawizard
## as.double.parameters_skewness          datawizard

```

```
## as.double.parameters_smoothness datawizard
## as.numeric.parameters_kurtosis datawizard
## as.numeric.parameters_skewness datawizard
## as.numeric.parameters_smoothness datawizard
## print.parameters_distribution datawizard
## print.parameters_kurtosis datawizard
## print.parameters_skewness datawizard
## summary.parameters_kurtosis datawizard
## summary.parameters_skewness datawizard

## #refugeeswelcome

library(dplyr) #various functions
```

EXPERIMENT ONE

Data

Read in the data. This is the coded and tidy version, with outliers removed.

```
exp1data = read.csv("exp1-coded-data.csv")
exp1data$vowelheard = as.factor(exp1data$vowelheard)
exp1data$block = as.factor(exp1data$block)

# terminology
exp1data$frame = exp1data$stimulustype
exp1data <- exp1data %>%
  mutate(frame = recode_factor(frame, targetdressreal = "DRESS",
targetkitreal = "KIT")) %>%
  mutate(firstanimal = recode_factor(firstanimal, horse1 = "horse",
kanga="kanga", kiwi = "kiwi"))
```

Early modeling of experiment 1 revealed speaker intercepts lead to convergence issues, and explained little variance, so they were dropped. All models have intercepts for participant and word.

Here is the syntax for the preregistered version:

```
PREMODELSTARTINGPOINT = glmer(vowelheard ~ scaledorderwithin * block + frame
* animal * presentationtype + (1 | id) + (1 | word), family = "binomial",
data = exp1data[exp1data$condition == "prime",])

PREMODELFINAL = glmer(vowelheard ~ scaledorderwithin + block +
presentationtype*frame + (1 | id) + (1 | word), family = "binomial", data =
exp1data[exp1data$condition == "prime",])
```

This shows an effect of presentationtype, in interaction with frame. There are more KIT-consistent responses when animals are incidental than when they are speaking. The important thing, though, is that the animal itself is not significant. Moreover, exploratory

analysis reveals that the first animal seen seems to have a lasting effect, and this model is obscuring important structure. We therefore turn to a modelling procedure that is sensitive to block differences.

Exploratory modeling revealed there was a strong effect of the animal shown in the first prime block, that persisted into the other block (for example modeling the blocks separately gives effects of 'animal' in block 1 but not block 2 or block 3. The strongest effect on block 2 and 3 seemed to be the first animal seen). To test effects of 'animal' and 'first animal' systematically, we created a binary factor for whether the participant was in the first block or not, then fit down from the following model:

```
explinitialmodel = glmer(vowelheard ~ primetype * presentationtype *  
(firstblock + frame + scaledorderwithin) + firstanimal * presentationtype *  
(firstblock + frame + scaledorderwithin) + (1 + frame | id) + (1 | word), family  
= "binomial", data = expldata$condition == "baseline",)
```

We removed interactions and tested the effect of the removal by comparison between minimally different models.

We fit a model of this structure for the baseline people and the prime people separately.

Baseline

Here is the final model arrived at for the baseline data. The effects of primetype, and of the firstanimal seen, are removed from the model as they have no significant effect.

```
EXP1FINALBASELINEMODEL = glmer(vowelheard ~ firstblock + frame + (1 + frame |  
id) + (1 | word), family = "binomial", data = expldata[expldata$condition ==  
"baseline",])
```

Table of effects:

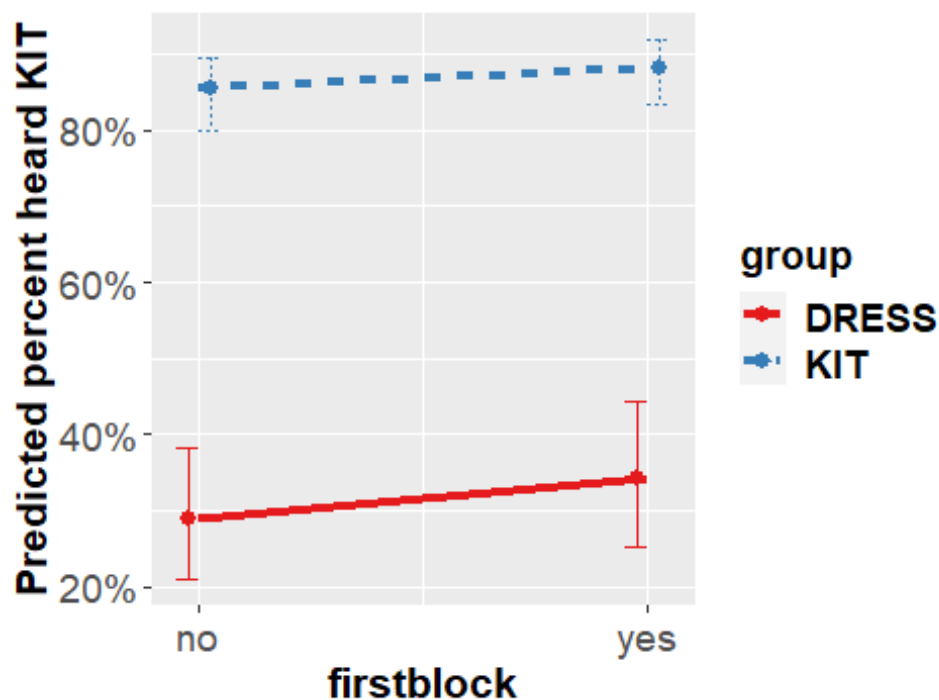
```
summary(EXP1FINALBASELINEMODEL)  
  
## Generalized linear mixed model fit by maximum likelihood (Laplace  
## Approximation) [glmerMod]  
## Family: binomial ( logit )  
## Formula: vowelheard ~ firstblock + frame + (1 + frame | id) + (1 | word)  
## Data: expldata[expldata$condition == "baseline", ]  
##  
##      AIC      BIC   logLik deviance df.resid  
## 4782.5  4828.0 -2384.3  4768.5     4853  
##  
## Scaled residuals:  
##      Min       1Q   Median       3Q      Max  
## -5.2488 -0.5418  0.2269  0.5082  4.4500  
##  
## Random effects:  
## Groups Name         Variance Std.Dev. Corr  
## word  (Intercept) 0.9781   0.989  
## id    (Intercept) 1.1442   1.070
```

```
##           frameKIT      1.8955      1.377      -0.81
## Number of obs: 4860, groups:  word, 90; id, 54
##
## Fixed effects:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -0.89967    0.21559  -4.173 3.01e-05 ***
## firstblockyes  0.24526    0.07947   3.086 0.00203 **
## frameKIT      2.66419    0.29394   9.064 < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##              (Intr) frstbl
## firstblckys -0.131
## frameKIT    -0.736  0.016
```

Figure from baseline model

```
exp1baselineplot <- plot_model(EXP1FINALBASELINEMODEL, type = "eff", terms =
c("firstblock", "frame")) +
  ylab("Predicted percent heard KIT") +
  xlab("firstblock") +
  theme(legend.text = element_text(size=14, face="bold")) +
  theme(legend.title = element_text(size=14, face="bold")) +
  theme(axis.text = element_text(size=14)) +
  theme(axis.title.x = element_text(size=16, face="bold")) +
  theme(axis.title.y = element_text(size=16, face="bold")) +
  theme(strip.text.x = element_text(size=16, face="bold")) +
  ggtitle(" ") +
  aes(linetype=group, color=group) +
  geom_line(size = 1.5) +
  theme(plot.title = element_text(size=16, face="bold", hjust = 0.5))

exp1baselineplot
```



##Prime data

Here is the final model arrived at for the prime data.

```
FINALPRIMEMODEL = glmer(vowelheard ~ firstblock + scaledorderwithin + frame *
firstanimal + (1 | id) + (1 | word), family = "binomial", data =
exp1data[exp1data$condition == "prime",])
```

Summary (Table 4 in paper):

```
summary(FINALPRIMEMODEL)

## Generalized linear mixed model fit by maximum likelihood (Laplace
## Approximation) [glmerMod]
## Family: binomial ( logit )
## Formula: vowelheard ~ firstblock + scaledorderwithin + frame * firstanimal
## +
## (1 | id) + (1 | word)
## Data: exp1data[exp1data$condition == "prime", ]
##
##      AIC      BIC   logLik deviance df.resid
## 6023.1   6089.9  -3001.6   6003.1     5840
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -9.8865 -0.5934  0.2527  0.5793  4.1133
##
## Random effects:
```

```

## Groups Name      Variance Std.Dev.
## word  (Intercept) 0.8301   0.9111
## id    (Intercept) 0.5296   0.7277
## Number of obs: 5850, groups: word, 90; id, 65
##
## Fixed effects:
##
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)   -0.46902    0.20715  -2.264 0.023560 *
## firstblockyes    0.34007    0.07018   4.845 1.26e-06 ***
## scaledorderwithin -0.06911    0.03283  -2.105 0.035278 *
## frameKIT        2.07562    0.21987   9.440 < 2e-16 ***
## firstanimalkanga -0.27322    0.24418  -1.119 0.263166
## firstanimalkiwi  -0.84406    0.23991  -3.518 0.000435 ***
## frameKIT:firstanimalkanga 0.06594    0.16007   0.412 0.680372
## frameKIT:firstanimalkiwi 0.88564    0.16412   5.396 6.80e-08 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##              (Intr) frstbl scldrd frmKIT frstnmlkn frstnmlkw
## firstblkys    -0.116
## scldrdrwthn   -0.006 -0.001
## frameKIT      -0.503  0.020  0.005
## firstnmlkng   -0.471 -0.002 -0.003  0.079
## firstanmlkw   -0.478 -0.007  0.008  0.078  0.408
## frmKIT:frstnmlkn 0.129 -0.004  0.003 -0.302 -0.273   -0.111
## frmKIT:frstnmlkw 0.123  0.011 -0.014 -0.289 -0.107   -0.298
##              frmKIT:frstnmlkn
## firstblkys
## scldrdrwthn
## frameKIT
## firstnmlkng
## firstanmlkw
## frmKIT:frstnmlkn
## frmKIT:frstnmlkw 0.403

```

Interaction Plot (Figure 5 in paper)

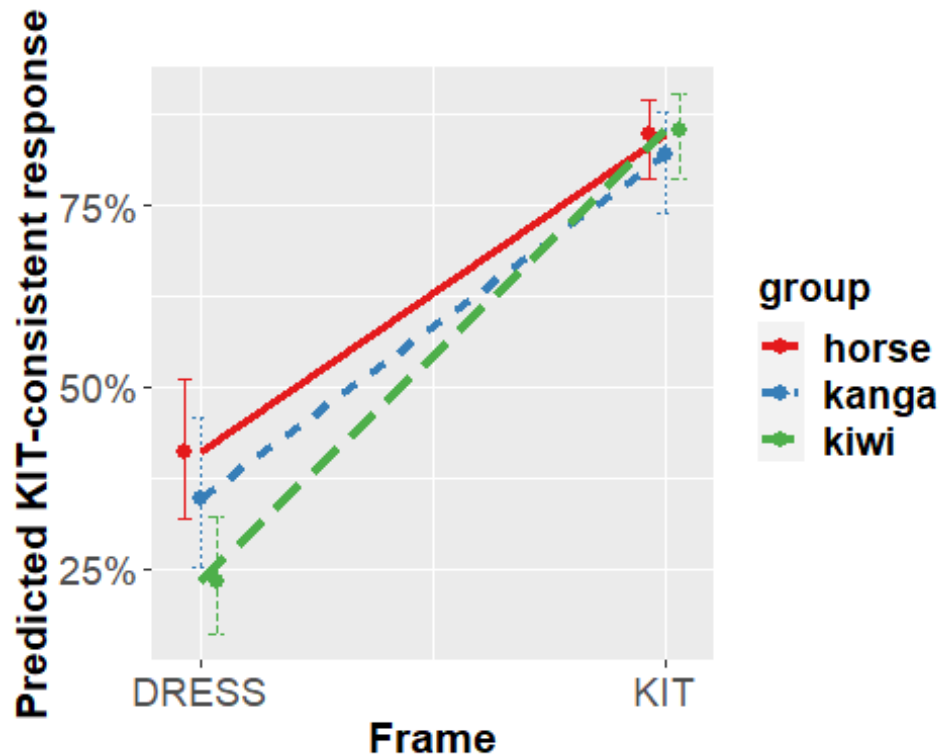
```

figure5<- plot_model(FINALPRIMEMODEL, type = "eff", terms = c("frame",
"firstanimal")) +
  ylab("Predicted KIT-consistent response")+
  xlab("Frame")+
  theme(legend.text = element_text(size=14, face="bold"))+
  theme(legend.title = element_text(size=14, face="bold"))+
  theme(axis.text = element_text(size=14))+
  theme(axis.title.x = element_text(size=16, face="bold")) +
  theme(axis.title.y = element_text(size=16, face="bold")) +
  theme(strip.text.x = element_text(size=16, face="bold")) +
  ggtitle(" ") +
  aes(linetype=group, color=group) +

```

```
geom_line(size = 1.5) +  
theme(plot.title = element_text(size=16, face="bold", hjust = 0.5))
```

figure5



Summary of experiment 1:

- There is no difference between the three horses.
- There is an effect of which of the horse/kangaroo/kiwi was seen in the first block, which persists through the experiment.
- This effect is within words where the DRESS vowel creates a real word. Words where KIT creates a real word are approaching ceiling, and are not affected by the prime.
- Interactions involving presentationtype are retained without the 'frame' slope, but don't converge. The frame slope leads presentationtype to be non-significant, but also leads to lack of convergence. To double check a role of presentation type, we therefore also fit separate models to the KIT and DRESS data, testing for an interaction between presentation type and the first animal seen. There is no effect.
- There is not a wide distribution of social characteristics (Australian attitudes and Australian exposure) and since we are already deviating significantly from our preregistration, we decided not to test these in this data-set, but rather to obtain a new data-set that would resolve some apparent problems with the experimental design. Assuming the design issues are rectified, we can look for social characteristics in the 2nd experiment.

In sum, there is good cause to believe the animal priming is having an effect, but it is also desirable to replicate this in a design that removes the blocked design, and the strong bias towards KIT.

EXPERIMENT TWO

Read in data

```
exp2target = read.csv("exp2target.csv")
exp2target$stimulustype = as.factor(exp2target$stimulustype)
exp2target$vowelheard = as.factor(exp2target$vowelheard)

targetKIT = filter(exp2target, stimulustype == "targetkitreal")
targetDRESS = filter(exp2target, stimulustype == "targetdressreal")
exp2target$frame = exp2target$stimulustype
exp2target <- exp2target %>%
  mutate(frame = recode_factor(frame, targetdressreal = "DRESS",
targetkitreal = "KIT")) %>%
  mutate(primetype = recode_factor(primetype, horse1 = "horse",
kanga="kanga", kiwi = "kiwi"))
```

Main model, no social effects (section 4.3.1)

Fitting down from a four way interaction, as described in the main text, we end up with this model.

```
exp2final = glmer(vowelheard ~ primetype * order_scaled * frame + (1 | id) +
(1 | word), family = "binomial", data = exp2target)
```

Table 6 summary:

```
summary(exp2final)

## Generalized linear mixed model fit by maximum likelihood (Laplace
## Approximation) [glmerMod]
## Family: binomial (logit)
## Formula: vowelheard ~ primetype * order_scaled * frame + (1 | id) + (1 |
## word)
## Data: exp2target
##
##      AIC      BIC   logLik deviance df.resid
##  9965.9  10068.0 -4969.0   9937.9    10866
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -12.1531  -0.4941   0.0739   0.4780  10.0826
##
## Random effects:
```

```

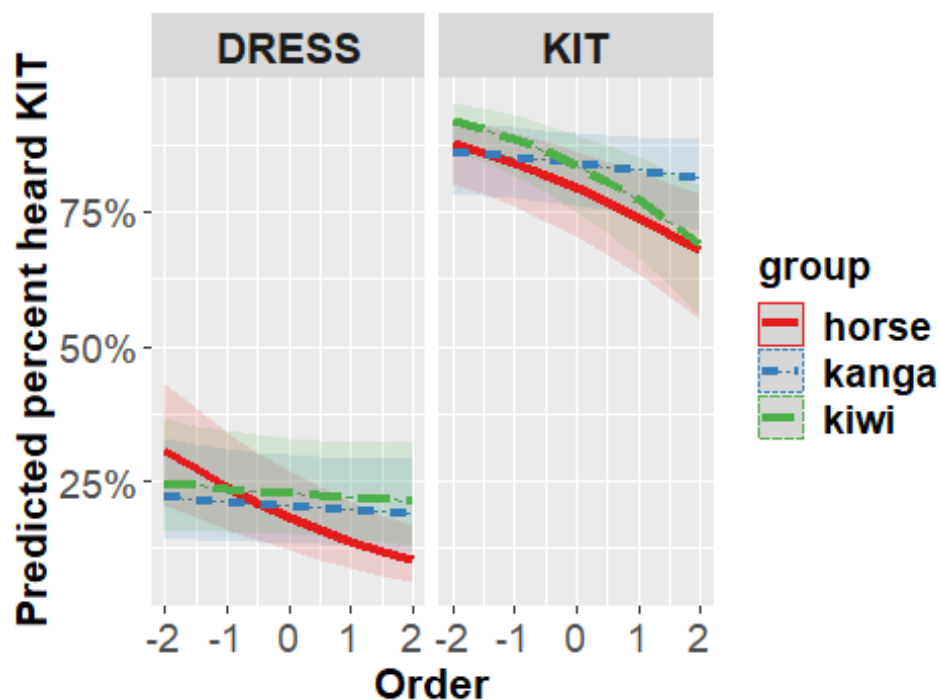
## Groups Name      Variance Std.Dev.
## id      (Intercept) 1.206    1.098
## word    (Intercept) 1.333    1.154
## Number of obs: 10880, groups: id, 136; word, 80
##
## Fixed effects:
##
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept) -1.486303   0.249005  -5.969 2.39e-09
***
## primetypkanga      0.133056   0.241838   0.550 0.582192
## primetypekiwi      0.271104   0.248956   1.089 0.276170
## order_scaled     -0.334437   0.061423  -5.445 5.19e-08
***
## frameKIT          2.836920   0.274635  10.330 < 2e-16
***
## primetypkanga:order_scaled      0.290805   0.086801   3.350 0.000807
***
## primetypekiwi:order_scaled      0.286146   0.089319   3.204 0.001357
**
## primetypkanga:frameKIT      0.174664   0.130484   1.339 0.180704
## primetypekiwi:frameKIT     -0.002285   0.132770  -0.017 0.986270
## order_scaled:frameKIT      0.028772   0.087950   0.327 0.743564
## primetypkanga:order_scaled:frameKIT -0.075474   0.125962  -0.599 0.549050
## primetypekiwi:order_scaled:frameKIT -0.388675   0.129348  -3.005 0.002657
**
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##              (Intr) prmtypkng prmtypkw ordr_s frmKIT prmtypkng:_
prmtypkw:_
## prmtypkng      -0.471
## prmtypkw      -0.458  0.471
## order_scald      0.027 -0.026  -0.025
## frameKIT      -0.551  0.060   0.059  -0.030
## prmtypkng:_    -0.019  0.024   0.018  -0.707  0.020
## prmtypkw:r_    -0.018  0.018   0.025  -0.688  0.020  0.486
## prmtypkng:KIT  0.121 -0.256  -0.121   0.056 -0.222 -0.055  -0.039
## prmtypkw:KIT  0.120 -0.123  -0.251   0.056 -0.219 -0.039  -0.054
## ordr_sc:KIT   -0.018  0.018   0.018  -0.698  0.001  0.494   0.480
## prmtypkng:_:KIT 0.012 -0.018  -0.012   0.487 -0.001 -0.690  -0.335
## prmtypkw:_:KIT 0.013 -0.012  -0.016   0.476 -0.004 -0.336  -0.691
##
##              prmtypkng:KIT prmtypkw:KIT o_:KIT prmtypkng:_:KIT
## prmtypkng
## prmtypkw
## order_scald
## frameKIT
## prmtypkng:_
## prmtypkw:r_
## prmtypkng:KIT

```

```
## prmtypkw:KIT    0.463
## ord_r_sc:KIT    -0.008    -0.008
## prmtypkn:_:KIT  0.009    0.005    -0.697
## prmtypkw:_:KIT  0.004    -0.029    -0.678    0.473
```

Figure 6 plot:

```
exp2plot <- plot_model(exp2final, type = "eff", terms = c("order_scaled",
"primetype", "frame")) +
  ylab("Predicted percent heard KIT") +
  xlab("Order") +
  theme(legend.text = element_text(size=14, face="bold")) +
  theme(legend.title = element_text(size=14, face="bold")) +
  theme(axis.text = element_text(size=14)) +
  theme(axis.title.x = element_text(size=16, face="bold")) +
  theme(axis.title.y = element_text(size=16, face="bold")) +
  theme(strip.text.x = element_text(size=16, face="bold")) +
  ggtitle(" ") +
  aes(linetype=group, color=group) +
  geom_line(size = 1.5) +
  theme(plot.title = element_text(size=16, face="bold", hjust = 0.5))
exp2plot
```



Social Factors (as reported in 4.3.2)

Description of process

There were problems with getting convergent models with this analysis, and there are 4 way interactions. Here is the process we ultimately followed to try and understand the patterns in the data. First, we modeled the two vowel types separately:

Step 1

We started with models of this structure, pruning down and checking anovas as we went.

```
exp1KITmodel = glmer(vowelheard ~ primetype * presentationtype * order_scaled
* (Gender + agelist + attitudemean + ausoveramonth) + (1 | id) + (1 | word),
family = "binomial", data = targetKIT)
```

and the same for DRESS.

The reason we started with this was because primetype x presentationtype was in the experimental design, and we wanted to see how this interacted with social characteristics. Early exploration also showed a very important effect of order, so we wanted to maintain the possibility that the timecourse was different for different social groups. We did not have enough data to look at interactions between social factors.

Through this process, we arrived at a model that was this

```
exp2KITmodelb = glmer(vowelheard ~ primetype * presentationtype *
order_scaled
* Gender + (1 | id) + (1 | word), family = "binomial", data = targetKIT)

## fixed-effect model matrix is rank deficient so dropping 8 columns /
coefficients

## Warning in checkConv(attr(opt, "derivs"), opt$par, ctrl =
control$checkConv, :
## Model failed to converge with max|grad| = 0.0407689 (tol = 0.002,
component 1)
```

Similarly for DRESS.

This was significantly better than an equivalent model that retained all three way interactions between these components, however it did not converge. So we need to explore this 4 way interaction in a way that can get convergence.

Step 2

To explore this further, and try and get convergent models, we then fit separate models for men and women. For women, the best model dropped presentation type completely, and retained a simple interaction between order and primetype. For men, the model with the

three way interaction was better than a model with 2 way interactions by an anova comparison, but still did not converge. Removing the three way interaction makes the model converge, and also shows no residual effect of presentation type. We therefore remove presentationtype from the model, concluding that we do not have sufficient data to reliably assess this 3 way interaction between presentation type, order, and primetype for men. Only 5 men, for example saw the horse in incidental mode, and only 6 saw the kangaroo speaking. We simply have more men than women.

This left us with four separate models for men and women, for KIT and DRESS, each showing a significant effect of order * prime type. We note that if we try to return to an overall model and examine order * primetype * Gender, this appears significant, but also does not converge. Again, this is no doubt due to data sparsity for men as compared to women. It is certainly the case that the women's data is more reliable.

In sum: What we definitely have at this stage is a robust order x primetype effect in both groups.

Step 3

Since the resultant models for men and for women did not look markedly different for KIT and DRESS, we then combined these back into a single model for each of men and women. For both men and women we end up with interactions between order, stimulustype and primetype in convergent models.

Step 4.

Our initial modelling didn't test interactions between social factors, since that would lead to complex interactions. But now we have relatively simple models, and they are separate for men and women, allowing us to test, within men and women, whether social factors play any role. The starting point for this exploration was:

```
womenbothsocial = glmer(vowelheard ~ (primetype + order_scaled +  
stimulustype)^3 * (agelist + attitudemean + ausoveramonth) + (1 | id) + (1  
| word), family = "binomial", data = exp2target[exp2target$Gender == "  
woman",])
```

(and same for men)

For men, all of the social characteristics fall out and we are back where we were at the end of step 3. For women, lots of the social characteristics appear to play a role, but we have non-convergent models. We abandon a 'step down' model and test possible 3 way interactions involving the new social characteristics in a step up fashion. Many don't converge, but we have two three way interactions that will converge: attitude x stimtype x primetype and ausoveramonth x stimtype x primetype. They won't converge in the same model as each other, and the interaction with ausoveramonth is much stronger. So we prune down the attitude interaction in order to get a convergent model.

Step 5

As a final step we removed the horse from our final models to check that the horse wasn't driving the significance we saw. It wasn't for the men. It was for one of the interactions for the women (order x primetype).

SUMMARY

These are our final two Exp 2 models.

```
menfinalmodel = glmer(vowelheard ~ (primetype + order_scaled + frame)^2 +  
(1 | id) + (1 | word), family = "binomial", data =  
exp2target[exp2target$Gender == "man",])
```

```
womenfinalmodel = glmer(vowelheard ~ primetype * order_scaled + primetype *  
frame * ausoveramonth + (1 | id) + (1 | word), family = "binomial", data =  
exp2target[exp2target$Gender == "woman",])
```

Model summaries:

```
summary(menfinalmodel)  
  
## Generalized linear mixed model fit by maximum likelihood (Laplace  
## Approximation) [glmerMod]  
## Family: binomial ( logit )  
## Formula: vowelheard ~ (primetype + order_scaled + frame)^2 + (1 | id) +  
## (1 | word)  
## Data: exp2target[exp2target$Gender == "man", ]  
##  
##      AIC      BIC   logLik deviance df.resid  
## 3259.6  3333.0 -1617.8  3235.6     3348  
##  
## Scaled residuals:  
##      Min       1Q   Median       3Q      Max  
## -6.8195 -0.5207  0.0972  0.5058  7.1136  
##  
## Random effects:  
## Groups Name      Variance Std.Dev.  
## word  (Intercept) 1.0481   1.0238  
## id    (Intercept) 0.9987   0.9993  
## Number of obs: 3360, groups: word, 80; id, 42  
##  
## Fixed effects:  
##  
##              Estimate Std. Error z value Pr(>|z|)  
## (Intercept) -2.119866   0.361188 -5.869 4.38e-09 ***  
## primetypekanga 1.516616   0.423575  3.581 0.000343 ***  
## primypekiwi    0.743461   0.426041  1.745 0.080977 .  
## order_scaled   0.170664   0.104757  1.629 0.103285  
## frameKIT       3.002664   0.297752 10.084 < 2e-16 ***  
## primetypekanga:order_scaled -0.005958 0.117264 -0.051 0.959481
```

```

## primetypekiwi:order_scaled -0.397880 0.120173 -3.311 0.000930 ***
## primetypekanga:frameKIT -0.833043 0.238665 -3.490 0.000482 ***
## primetypekiwi:frameKIT 0.068049 0.248052 0.274 0.783828
## order_scaled:frameKIT -0.356341 0.093520 -3.810 0.000139 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
## (Intr) prmtypkpn prmtypkw ord_r_s frmKIT prmtypkpn:_ prmtypkw:_
## primetypkng -0.678
## primetypekw -0.672 0.573
## order_scaled -0.028 0.023 0.025
## frameKIT -0.447 0.169 0.164 0.019
## prmtypkng:_ 0.020 -0.018 -0.018 -0.724 -0.008
## prmtypkw:r_ 0.024 -0.019 -0.010 -0.683 -0.015 0.583
## prmtypkpn:KIT 0.242 -0.298 -0.203 -0.015 -0.488 0.000 0.011
## prmtypkw:KIT 0.228 -0.195 -0.311 -0.008 -0.462 0.009 -0.052
## ord_r_sc:KIT 0.013 -0.009 -0.012 -0.512 -0.027 0.123 0.084
## prmtypkpn:KIT prmtypkw:KIT
## primetypkng
## primetypekw
## order_scaled
## frameKIT
## prmtypkng:_
## prmtypkw:r_
## prmtypkpn:KIT
## prmtypkw:KIT 0.582
## ord_r_sc:KIT 0.005 -0.010

summary(womenfinalmodel)

## Generalized linear mixed model fit by maximum likelihood (Laplace
## Approximation) [glmerMod]
## Family: binomial ( logit )
## Formula:
## vowelheard ~ primetype * order_scaled + primetype * frame * ausoveramonth
## +
## (1 | id) + (1 | word)
## Data: exp2target[exp2target$Gender == " woman", ]
##
## AIC BIC logLik deviance df.resid
## 6667.8 6785.2 -3316.9 6633.8 7343
##
## Scaled residuals:
## Min 1Q Median 3Q Max
## -11.0164 -0.4819 -0.0579 0.4687 7.0339
##
## Random effects:
## Groups Name Variance Std.Dev.
## id (Intercept) 1.069 1.034

```

```

## word (Intercept) 1.447 1.203
## Number of obs: 7360, groups: id, 92; word, 80
##
## Fixed effects:
##
## Estimate Std. Error z value
Pr(>|z|)
## (Intercept) -1.35962 0.29712 -4.576 4.74e-
06 ***
## primetypekanga -0.95846 0.33597 -2.853
0.004334 **
## primypekiwi 0.19187 0.34138 0.562
0.574083
## order_scaled -0.40886 0.05103 -8.013 1.12e-
15 ***
## frameKIT 2.79956 0.29885 9.368 < 2e-
16 ***
## ausoveramonthy 0.17410 0.38351 0.454
0.649846
## primetypekanga:order_scaled 0.31001 0.07772 3.989 6.64e-
05 ***
## primypekiwi:order_scaled 0.30337 0.07866 3.857
0.000115 ***
## primetypekanga:frameKIT 1.03781 0.19960 5.199 2.00e-
07 ***
## primypekiwi:frameKIT -0.02314 0.18889 -0.123
0.902489
## primetypekanga:ausoveramonthy 1.45815 0.60017 2.430
0.015118 *
## primypekiwi:ausoveramonthy -0.63048 0.64865 -0.972
0.331052
## frameKIT:ausoveramonthy 0.04974 0.21565 0.231
0.817579
## primetypekanga:frameKIT:ausoveramonthy -1.23567 0.34439 -3.588
0.000333 ***
## primypekiwi:frameKIT:ausoveramonthy -0.28496 0.35413 -0.805
0.421000
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

##
## Correlation matrix not shown by default, as p = 15 > 12.
## Use print(x, correlation=TRUE) or
## vcov(x) if you need it

```

These are the plots for figure 7 and figure 8:

```

Exp2plotwomen1 <- plot_model(womenfinalmodel, type = "eff", terms =
c("order_scaled", "primetype")) +
  ylab("Predicted percent heard KIT") +
  xlab("Scaled Order in Experiment") +

```



```

theme(legend.text = element_text(size=14, face="bold"))+
theme(legend.title = element_text(size=14, face="bold"))+
theme(axis.text = element_text(size=14))+
theme(axis.title.x = element_text(size=16, face="bold")) +
theme(axis.title.y = element_text(size=16, face="bold")) +
theme(strip.text.x = element_text(size=16, face="bold")) +
ggtitle(" ") +
aes(linetype=group, color=group) +
geom_line(size = 1.5) +
theme(plot.title = element_text(size=16, face="bold", hjust = 0.5))

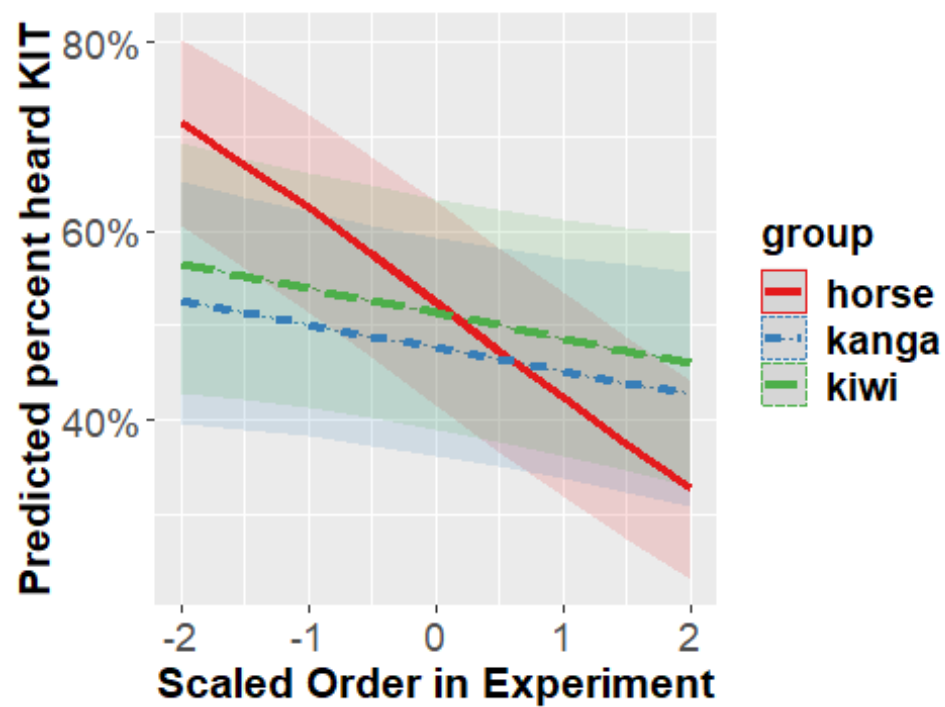
```

```

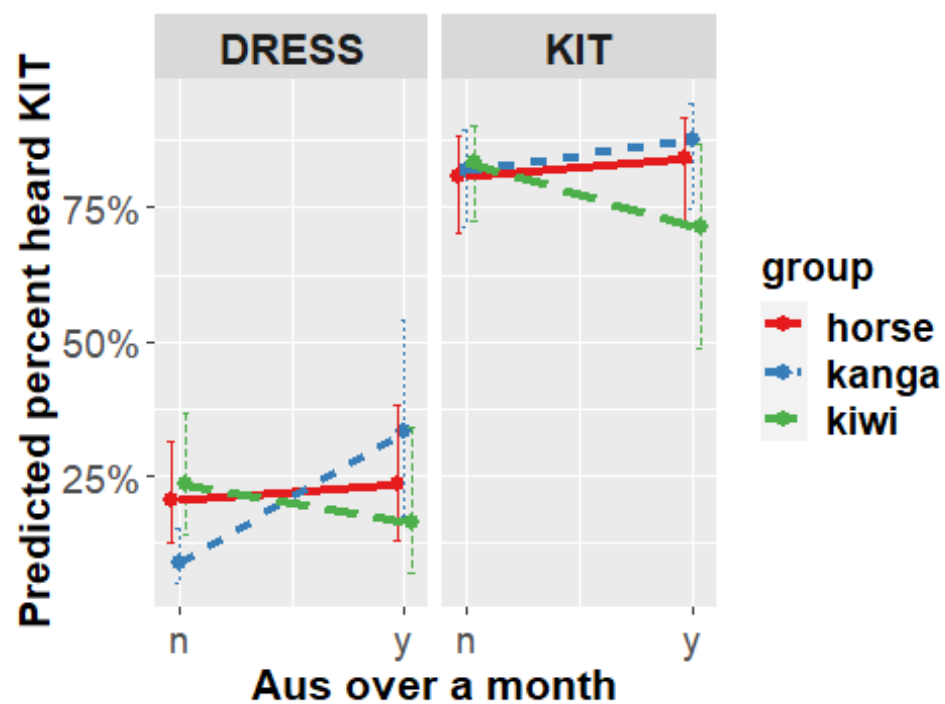
Exp2plotwomen2 <- plot_model(womenfinalmodel, type = "eff", terms =
c("auvermonth", "primetype", "frame")) +
  ylab("Predicted percent heard KIT")+
  xlab("Aus over a month") +
  theme(legend.text = element_text(size=14, face="bold"))+
  theme(legend.title = element_text(size=14, face="bold"))+
  theme(axis.text = element_text(size=14))+
  theme(axis.title.x = element_text(size=16, face="bold")) +
  theme(axis.title.y = element_text(size=16, face="bold")) +
  theme(strip.text.x = element_text(size=16, face="bold")) +
  ggtitle(" ") +
  aes(linetype=group, color=group) +
  geom_line(size = 1.5) +
  theme(plot.title = element_text(size=16, face="bold", hjust = 0.5))

```

Exp2plotwomen1



Exp2plotwomen2



```
Exp2plotmen1 <- plot_model(menfinalmodel, type = "eff", terms =
c("order_scaled", "primetype", "frame")) +
  ylab("Predicted percent heard KIT") +
  xlab("Scaled Order in Experiment") +
  theme(legend.text = element_text(size=14, face="bold")) +
  theme(legend.title = element_text(size=14, face="bold")) +
  theme(axis.text = element_text(size=14)) +
  theme(axis.title.x = element_text(size=16, face="bold")) +
  theme(axis.title.y = element_text(size=16, face="bold")) +
  theme(strip.text.x = element_text(size=16, face="bold")) +
  ggtitle(" ") +
  aes(linetype=group, color=group) +
  geom_line(size = 1.5) +
  theme(plot.title = element_text(size=16, face="bold", hjust = 0.5))
Exp2plotmen1
```

