

Online Methods Data Analysis

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Load the necessary libraries, try to remove the ones that aren't necessary because they cause intense conflicts. Curses on anyone who loads `plyr` unnecessarily.

```
library(tidyverse)
```

```
## -- Attaching packages ----- tidyverse 1.3.0 --

## v ggplot2 3.3.3      v purrr  0.3.4
## v tibble  3.1.2      v dplyr  1.0.6
## v tidyr   1.0.0      v stringr 1.4.0
## v readr   1.3.1      v forcats 0.4.0

## Warning: package 'ggplot2' was built under R version 3.6.2

## Warning: package 'tibble' was built under R version 3.6.2

## Warning: package 'purrr' was built under R version 3.6.2

## Warning: package 'dplyr' was built under R version 3.6.2

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

```
library(effsize)
```

```
## Warning: package 'effsize' was built under R version 3.6.2
```

```
library(effectsize)
```

```
## Warning: package 'effectsize' was built under R version 3.6.2
```

```
library(epitools)
```

```
##
## Attaching package: 'epitools'

## The following objects are masked from 'package:effectsize':
##
##      oddsratio, riskratio
```

```
library(boot)
library(lme4)
```

```
## Loading required package: Matrix
```

```
##
## Attaching package: 'Matrix'
```

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

```
library(ggpubr)
```

```
## Warning: package 'ggpubr' was built under R version 3.6.2
```

```
## Registered S3 methods overwritten by 'car':
##   method                from
##   influence.merMod       lme4
##   cooks.distance.influence.merMod lme4
##   dfbeta.influence.merMod lme4
##   dfbetas.influence.merMod lme4
```

```
library(gridExtra)
```

```
##
## Attaching package: 'gridExtra'
```

```
## The following object is masked from 'package:dplyr':
##
##   combine
```

```
library(plotrix)
library(EMAtools) #for deriving effect sizes
require(reshape2) # for woo/spelke
```

```
## Loading required package: reshape2
```

```
##
## Attaching package: 'reshape2'
```

```
## The following object is masked from 'package:tidyr':
##
##   smiths
```

```
require(cowplot) # for big plot
```

```
## Loading required package: cowplot
```

```
##
## *****

## Note: As of version 1.0.0, cowplot does not change the

## default ggplot2 theme anymore. To recover the previous

## behavior, execute:
## theme_set(theme_cowplot())

## *****

##
## Attaching package: 'cowplot'

## The following object is masked from 'package:ggpubr':
##
## get_legend

library(metafor) # for meta-analysis?

## Loading 'metafor' package (version 2.4-0). For an overview
## and introduction to the package please type: help(metafor).
```

Individual Data analysis

Liu Spelke Data Analysis

Data reading

```
combined.data.long <- read.csv("data/liu_spelke_data.csv") %>%
  filter(subj != "P13") %>% # no data for test trials
  mutate_if(is.character, as.factor) %>%
  mutate(sample = recode(sample, "lab" = "In-Person",
                           "online" = "Online")) %>%
  mutate(trialtype = recode(trialtype,
                           "exp" = "Expected",
                           "unexp" = "Unexpected"))

sample.info <- combined.data.long %>%
  distinct(subj, .keep_all = TRUE) %>%
  group_by(sample) %>%
  summarize(mean = mean(agem), min=range(agem)[1], max=range(agem)[2], n=length(unique(subj)), f=sum(se

# average looking times
final.repl.data.avg <- combined.data.long %>%
  filter(!is.na(trialtype)) %>%
  group_by(sample, subj, trialtype) %>%
  summarise(avg_look = mean(look, na.rm=TRUE))
```

`summarise()` has grouped output by 'sample', 'subj'. You can override using the `.groups` argument.

In-person Results

```
test.avg <- final.repl.data.avg %>%  
  filter(trialtype != "famhab") %>%  
  mutate(loglook = log(avg_look))  
test.avg$trialtype <- relevel(test.avg$trialtype, ref = "Expected")  
  
orig.avg <- test.avg %>% filter(sample=="In-Person")  
  
orig.m1 <- lmer(loglook ~ trialtype + (1|subj),  
  data = orig.avg)  
orig.m1.std <- lmer(scale(loglook) ~ trialtype + (1|subj),  
  data = orig.avg)
```

Online Results

```
online.avg <- test.avg %>% filter(sample=="Online")  
  
online.m1 <- lmer(loglook ~ trialtype + (1|subj),  
  data = online.avg)  
  
online.m1.cooks <- lmer(loglook ~ trialtype + (1|subj),  
  data = online.avg %>% filter(subj != "P7-"))  
  
online.m1.std <- lmer(scale(loglook) ~ trialtype + (1|subj),  
  data = online.avg %>% filter(subj != "P7-"))
```

Woo Spelke Data Analysis

Experiment 1: Evaluations based on preferential reaching

```
# data organization  
choice <- matrix(c(17, 5, 5, 19), ncol = 2, byrow = T)  
rownames(choice) <- c("True Belief", "False Belief")  
colnames(choice) <- c("Positive-Outcome", "Unhelpful-Outcome")  
  
# visualize data  
## using ggplot2  
choice.d <- as.data.frame(choice)  
choice.d$Condition <- c("True Belief", "False Belief")  
choice.dm <- reshape2::melt(choice.d, id.vars = 'Condition')  
choice.dm$Condition <- as.factor(choice.dm$Condition)  
  
choice.dm$Condition <- relevel(choice.dm$Condition, "True Belief")  
levels(choice.dm$variable)  
  
## [1] "Positive-Outcome" "Unhelpful-Outcome"
```

```

choice.dm$variable <- relevel(choice.dm$variable, "Unhelpful-Outcome")
levels(choice.dm$variable) <- c("Unhelpful-Outcome", "Positive-Outcome")

choice.dm$variable.n <- choice.dm$variable
levels(choice.dm$variable.n) <- c("Unhelpful-\nOutcome", "Helpful-\nOutcome")

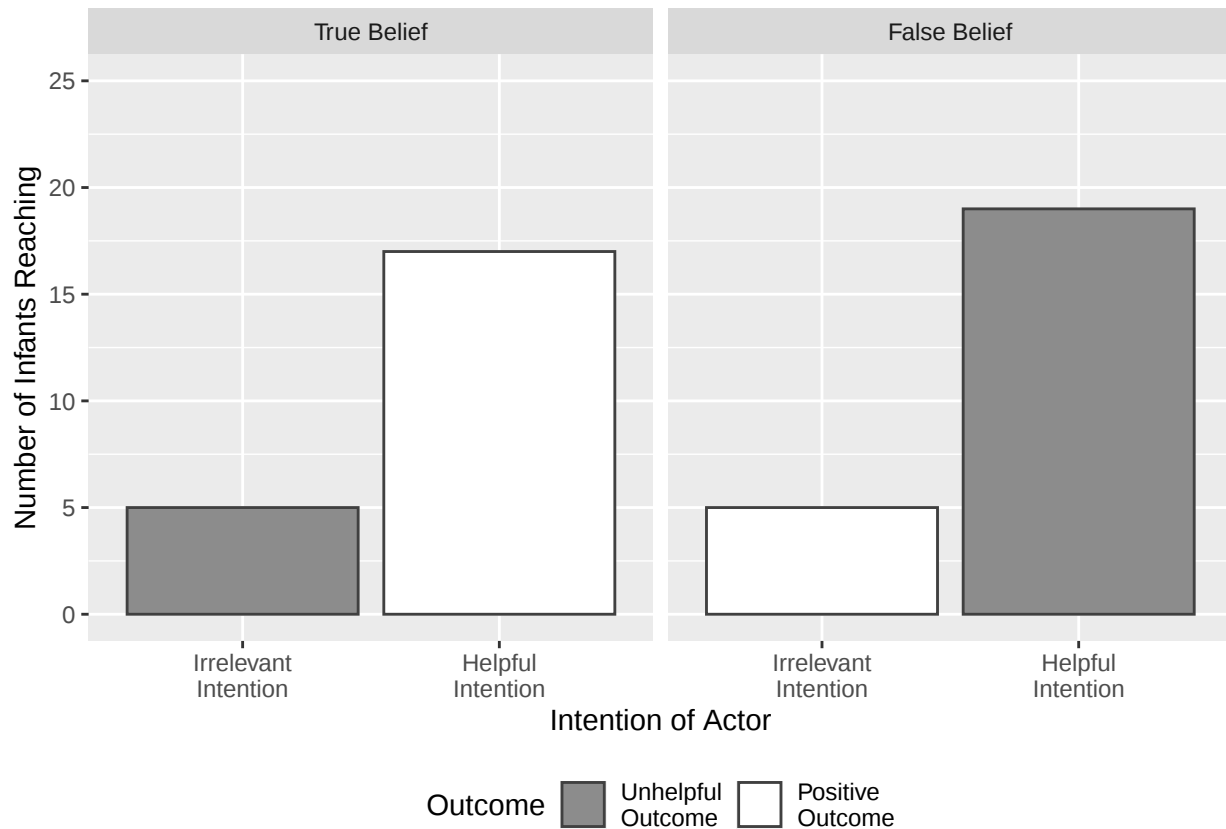
for (i in 1:nrow(choice.dm)) {
  if (choice.dm$Condition[i] == "True Belief") {
    if (choice.dm$variable[i] == "Positive-Outcome") {
      choice.dm$intention[i] <- "Helpful\nIntention"
    }
    else if (choice.dm$variable[i] == "Unhelpful-Outcome") {
      choice.dm$intention[i] <- "Irrelevant\nIntention"
    }
  }
  else if (choice.dm$Condition[i] == "False Belief") {
    if (choice.dm$variable[i] == "Positive-Outcome") {
      choice.dm$intention[i] <- "Irrelevant\nIntention"
    }
    else if (choice.dm$variable[i] == "Unhelpful-Outcome") {
      choice.dm$intention[i] <- "Helpful\nIntention"
    }
  }
}

for (i in 1:nrow(choice.dm)) {
  if (choice.dm$variable[i] == "Positive-Outcome") {
    choice.dm$outcome[i] <- "Positive\nOutcome"
  }
  else if (choice.dm$variable[i] == "Unhelpful-Outcome") {
    choice.dm$outcome[i] <- "Unhelpful\nOutcome"
  }
}

choice.dm$intention <- as.factor(choice.dm$intention)
choice.dm$intention <- relevel(choice.dm$intention, "Irrelevant\nIntention")
choice.dm$outcome <- as.factor(choice.dm$outcome)
choice.dm$outcome <- relevel(choice.dm$outcome, "Unhelpful\nOutcome")

ggplot(choice.dm, aes(intention, value)) + # grouped
  geom_bar(aes(fill = outcome), position = "dodge", stat="identity", color = "grey25") +
  facet_wrap(~Condition, scales = "free_x") +
  scale_fill_manual(values = c("grey55", "grey100")) +
  labs(x = "Intention of Actor", fill = "Outcome", y = "Number of Infants Reaching") +
  theme(legend.position = "bottom") +
  ylim(c(0,25)) # Figure 2A; code for paper; new labels (intention and outcome both present)

```



```
# binomial tests
## pref for Positive-Intention vs. Irrelevant-Intention (main test)
binom.test(17, n = 22, p = .5, alternative = "two.sided") # True Belief

##
## Exact binomial test
##
## data: 17 and 22
## number of successes = 17, number of trials = 22, p-value = 0.0169
## alternative hypothesis: true probability of success is not equal to 0.5
## 95 percent confidence interval:
## 0.5462964 0.9217937
## sample estimates:
## probability of success
## 0.7727273

RR.TB <- 17/22/0.5 # RR = relative risk

binom.test(19, n = 24, p = .5, alternative = "two.sided") # False Belief

##
## Exact binomial test
##
## data: 19 and 24
## number of successes = 19, number of trials = 24, p-value = 0.006611
## alternative hypothesis: true probability of success is not equal to 0.5
```

```
## 95 percent confidence interval:
## 0.5784872 0.9286814
## sample estimates:
## probability of success
## 0.7916667
```

```
RR.FB <- 19/24/0.5
```

```
# chi-square test: Difference in choice based on outcome, by condition (main text)
chisq.test(matrix(c(19,5,5,17), ncol = 2, byrow = T))
```

```
##
## Pearson's Chi-squared test with Yates' continuity correction
##
## data: matrix(c(19, 5, 5, 17), ncol = 2, byrow = T)
## X-squared = 12.478, df = 1, p-value = 0.0004117
```

```
oddsratio.wald.outcome <- epitools::oddsratio.wald(matrix(c(19,5,5,17), ncol = 2, byrow = T))$measure[2]
# ES.h(17/22, 5/24) # Cohen's h
```

Experiment 2: Evaluations based on preferential looking

```
bh2zoom <- read.csv("data/woo_spelke_data.csv")
dim(bh2zoom)
```

```
## [1] 48 15
```

```
# participant details (main text)
summary(bh2zoom$Age.Decimal)
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## 14.33  14.63   14.90   14.91  15.11   15.67
```

```
bh2zoom$Condition <- as.factor(bh2zoom$Condition)
levels(bh2zoom$Condition) <- c("False Belief", "True Belief")
by(bh2zoom$Age.Decimal, bh2zoom$Condition, summary)
```

```
## bh2zoom$Condition: False Belief
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## 14.37  14.66   14.82   14.88  15.08   15.67
## -----
## bh2zoom$Condition: True Belief
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## 14.33  14.60   14.92   14.93  15.15   15.67
```

```
table(bh2zoom$Sex)
```

```
##
## F M
## 26 22
```

```
by(bh2zoom$Sex, bh2zoom$Condition, table)
```

```
## bh2zoom$Condition: False Belief
```

```
##
```

```
## F M
```

```
## 11 13
```

```
## -----
```

```
## bh2zoom$Condition: True Belief
```

```
##
```

```
## F M
```

```
## 15 9
```

```
# data organization
```

```
names(bh2zoom)
```

```
## [1] "Relabeled.Script"      "Script"
## [3] "Subject.ID"            "Sex"
## [5] "Age...Month"           "Age...Day"
## [7] "Age.Decimal"           "Condition"
## [9] "Fam.Box.Color"         "Pink.Actor.Show.Side"
## [11] "Pink.Actor.Order"      "Test.Actor.Old.Toy.Color"
## [13] "Pink.Actor.Choice.Side" "ChoiceLeft"
## [15] "ChoiceRight"
```

```
for (i in 1:nrow(bh2zoom)) {
  if (bh2zoom$Test.Actor.Old.Toy.Color[i] == "Pink") {
    if (bh2zoom$Pink.Actor.Choice.Side[i] == "Left") {
      bh2zoom$ChoicePositive0[i] <- bh2zoom$ChoiceLeft[i]
      bh2zoom$ChoiceUnhelpful0[i] <- bh2zoom$ChoiceRight[i]
    }
    else if (bh2zoom$Pink.Actor.Choice.Side[i] == "Right") {
      bh2zoom$ChoicePositive0[i] <- bh2zoom$ChoiceRight[i]
      bh2zoom$ChoiceUnhelpful0[i] <- bh2zoom$ChoiceLeft[i]
    }
  }
  else if (bh2zoom$Test.Actor.Old.Toy.Color[i] == "Yellow") {
    if (bh2zoom$Pink.Actor.Choice.Side[i] == "Right") {
      bh2zoom$ChoicePositive0[i] <- bh2zoom$ChoiceLeft[i]
      bh2zoom$ChoiceUnhelpful0[i] <- bh2zoom$ChoiceRight[i]
    }
    else if (bh2zoom$Pink.Actor.Choice.Side[i] == "Left") {
      bh2zoom$ChoicePositive0[i] <- bh2zoom$ChoiceRight[i]
      bh2zoom$ChoiceUnhelpful0[i] <- bh2zoom$ChoiceLeft[i]
    }
  }
}
by(bh2zoom$ChoicePositive0, bh2zoom$Condition, summary)
```

```
## bh2zoom$Condition: False Belief
```

```
## Min. 1st Qu. Median Mean 3rd Qu. Max.
```

```
## 2.650 7.808 9.725 10.415 11.723 23.680
```

```
## -----
```

```
## bh2zoom$Condition: True Belief
##   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   4.070   9.793  12.500   13.257  16.617   22.500
```

```
by(bh2zoom$ChoicePositive0, bh2zoom$Condition, sd)
```

```
## bh2zoom$Condition: False Belief
## [1] 4.493414
## -----
## bh2zoom$Condition: True Belief
## [1] 4.82981
```

```
by(bh2zoom$ChoiceUnhelpful0, bh2zoom$Condition, summary)
```

```
## bh2zoom$Condition: False Belief
##   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   5.44   11.75   14.47   13.55   16.28   19.53
## -----
## bh2zoom$Condition: True Belief
##   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   3.300   6.505   8.905   9.378  11.607   18.240
```

```
by(bh2zoom$ChoiceUnhelpful0, bh2zoom$Condition, sd)
```

```
## bh2zoom$Condition: False Belief
## [1] 3.941788
## -----
## bh2zoom$Condition: True Belief
## [1] 4.073916
```

```
# convert to percentages
for (i in 1:nrow(bh2zoom)) {
  bh2zoom$pPositive0[i] <- bh2zoom$ChoicePositive0[i] / (bh2zoom$ChoiceUnhelpful0[i] + bh2zoom$ChoicePositive0[i])
  bh2zoom$pUnhelpful0[i] <- bh2zoom$ChoiceUnhelpful0[i] / (bh2zoom$ChoiceUnhelpful0[i] + bh2zoom$ChoicePositive0[i])
}

for (i in 1:nrow(bh2zoom)) {
  if (bh2zoom$Condition[i] == "True Belief") {
    bh2zoom$pHelpfulI[i] <- bh2zoom$pPositive0[i]
    bh2zoom$pIrrelevantI[i] <- bh2zoom$pUnhelpful0[i]
  }
  else if (bh2zoom$Condition[i] == "False Belief") {
    bh2zoom$pIrrelevantI[i] <- bh2zoom$pPositive0[i]
    bh2zoom$pHelpfulI[i] <- bh2zoom$pUnhelpful0[i]
  }
}

by(bh2zoom$pPositive0, bh2zoom$Condition, summary)
```

```
## bh2zoom$Condition: False Belief
##   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
```

```
## 0.1763 0.3371 0.4116 0.4293 0.4913 0.7949
## -----
## bh2zoom$Condition: True Belief
##   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## 0.3102 0.4985 0.6098 0.5829 0.6743 0.8721
```

```
by(bh2zoom$pPositive0, bh2zoom$Condition, sd)
```

```
## bh2zoom$Condition: False Belief
## [1] 0.1465029
## -----
## bh2zoom$Condition: True Belief
## [1] 0.1492586
```

```
by(bh2zoom$pUnhelpful0, bh2zoom$Condition, summary)
```

```
## bh2zoom$Condition: False Belief
##   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## 0.2051 0.5087 0.5884 0.5707 0.6629 0.8237
## -----
## bh2zoom$Condition: True Belief
##   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## 0.1279 0.3257 0.3902 0.4171 0.5015 0.6898
```

```
by(bh2zoom$pUnhelpful0, bh2zoom$Condition, sd)
```

```
## bh2zoom$Condition: False Belief
## [1] 0.1465029
## -----
## bh2zoom$Condition: True Belief
## [1] 0.1492586
```

```
by(bh2zoom$pHelpfulI, bh2zoom$Condition, summary)
```

```
## bh2zoom$Condition: False Belief
##   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## 0.2051 0.5087 0.5884 0.5707 0.6629 0.8237
## -----
## bh2zoom$Condition: True Belief
##   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## 0.3102 0.4985 0.6098 0.5829 0.6743 0.8721
```

```
by(bh2zoom$pHelpfulI, bh2zoom$Condition, sd)
```

```
## bh2zoom$Condition: False Belief
## [1] 0.1465029
## -----
## bh2zoom$Condition: True Belief
## [1] 0.1492586
```

```
by(bh2zoom$pIrrelevantI, bh2zoom$Condition, summary)
```

```
## bh2zoom$Condition: False Belief
##   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  0.1763  0.3371  0.4116  0.4293  0.4913  0.7949
## -----
## bh2zoom$Condition: True Belief
##   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  0.1279  0.3257  0.3902  0.4171  0.5015  0.6898
```

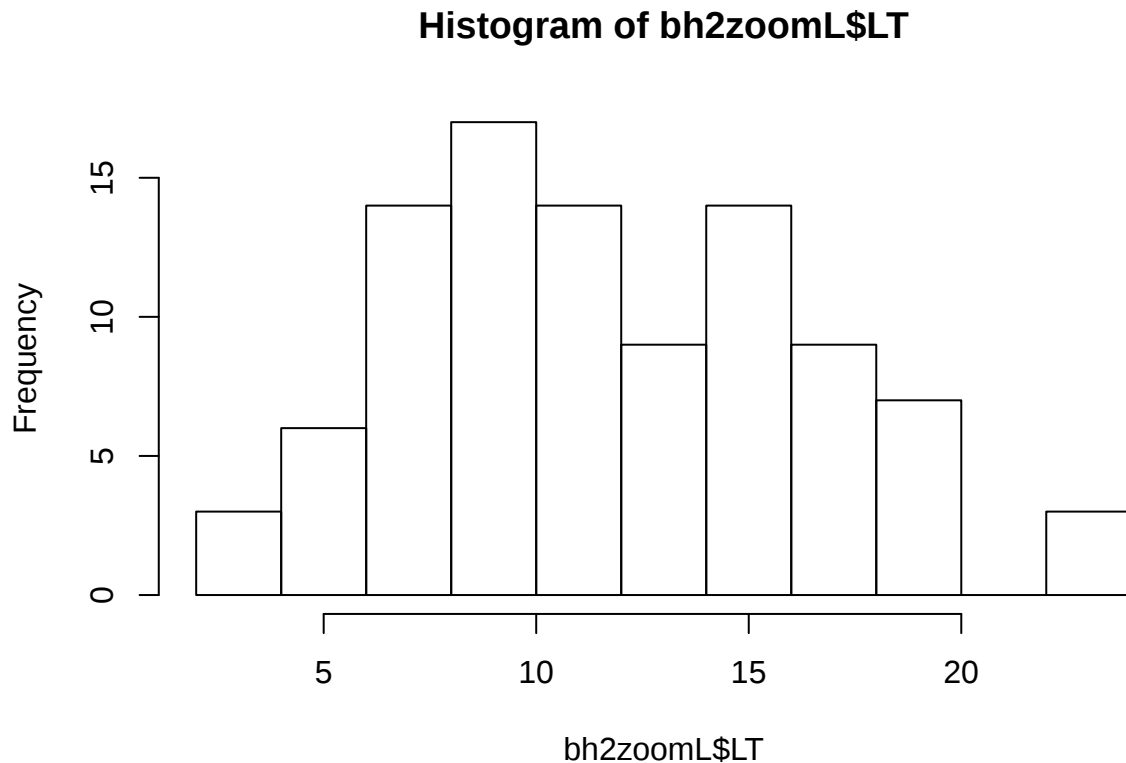
```
by(bh2zoom$pIrrelevantI, bh2zoom$Condition, sd)
```

```
## bh2zoom$Condition: False Belief
## [1] 0.1465029
## -----
## bh2zoom$Condition: True Belief
## [1] 0.1492586
```

```
# visualize raw looking times (Figure 2B)
bh2zoomL <- gather(bh2zoom, ActorType, LT,
                  ChoicePositive0, ChoiceUnhelpful0)
head(bh2zoomL)
```

```
##   Relabeled.Script Script Subject.ID Sex Age...Month Age...Day Age.Decimal
## 1                1b      9        p25  F         15         9      15.30000
## 2                2b     10        p17  F         15         0      15.00000
## 3                3b      5        p26  F         14        10      14.33333
## 4                4b     14        p13  F         15        11      15.36667
## 5                5b      3        p22  M         14        18      14.60000
## 6                6b     12        p15  M         14        25      14.83333
##   Condition Fam.Box.Color Pink.Actor.Show.Side Pink.Actor.Order
## 1 False Belief          Blue                Left                1
## 2 False Belief          Blue                Left                1
## 3 True Belief          Green                Left                2
## 4 False Belief          Green                Left                2
## 5 True Belief          Blue                Right                2
## 6 False Belief          Blue                Right                2
##   Test.Actor.Old.Toy.Color Pink.Actor.Choice.Side ChoiceLeft ChoiceRight
## 1                Pink                Left      15.29      12.49
## 2                Yellow                Left       7.60      18.51
## 3                Yellow                Left       9.87      17.94
## 4                Pink                Left      10.61      11.84
## 5                Pink                Right      11.66      12.55
## 6                Yellow                Right      10.03      16.96
##   pPositive0 pUnhelpful0 pIrrelevantI pHelpfulI ActorType LT
## 1  0.5503960  0.4496040  0.5503960  0.4496040 ChoicePositive0 15.29
## 2  0.7089238  0.2910762  0.7089238  0.2910762 ChoicePositive0 18.51
## 3  0.6450917  0.3549083  0.3549083  0.6450917 ChoicePositive0 17.94
## 4  0.4726058  0.5273942  0.4726058  0.5273942 ChoicePositive0 10.61
## 5  0.5183808  0.4816192  0.4816192  0.5183808 ChoicePositive0 12.55
## 6  0.3716191  0.6283809  0.3716191  0.6283809 ChoicePositive0 10.03
```

```
hist(bh2zoomL$LT)
```



```
class(bh2zoomL$ActorType)
```

```
## [1] "character"
```

```
bh2zoomL$ActorType <- as.factor(bh2zoomL$ActorType)
bh2zoomL$Condition <- as.factor(bh2zoomL$Condition)
levels(bh2zoomL$ActorType) <- c("Positive-Outcome", "Unhelpful-Outcome")
bh2zoomL$ActorType <- relevel(bh2zoomL$ActorType, "Unhelpful-Outcome")
bh2zoomL$Outcome <- bh2zoomL$ActorType
levels(bh2zoomL$Outcome) <- c("Unhelpful\nOutcome", "Positive\nOutcome") # note: this is reversed from
bh2zoomL$Condition <- relevel(bh2zoomL$Condition, "True Belief")
```

```
table(bh2zoomL$ActorType)
```

```
##
## Unhelpful-Outcome Positive-Outcome
##                48                48
```

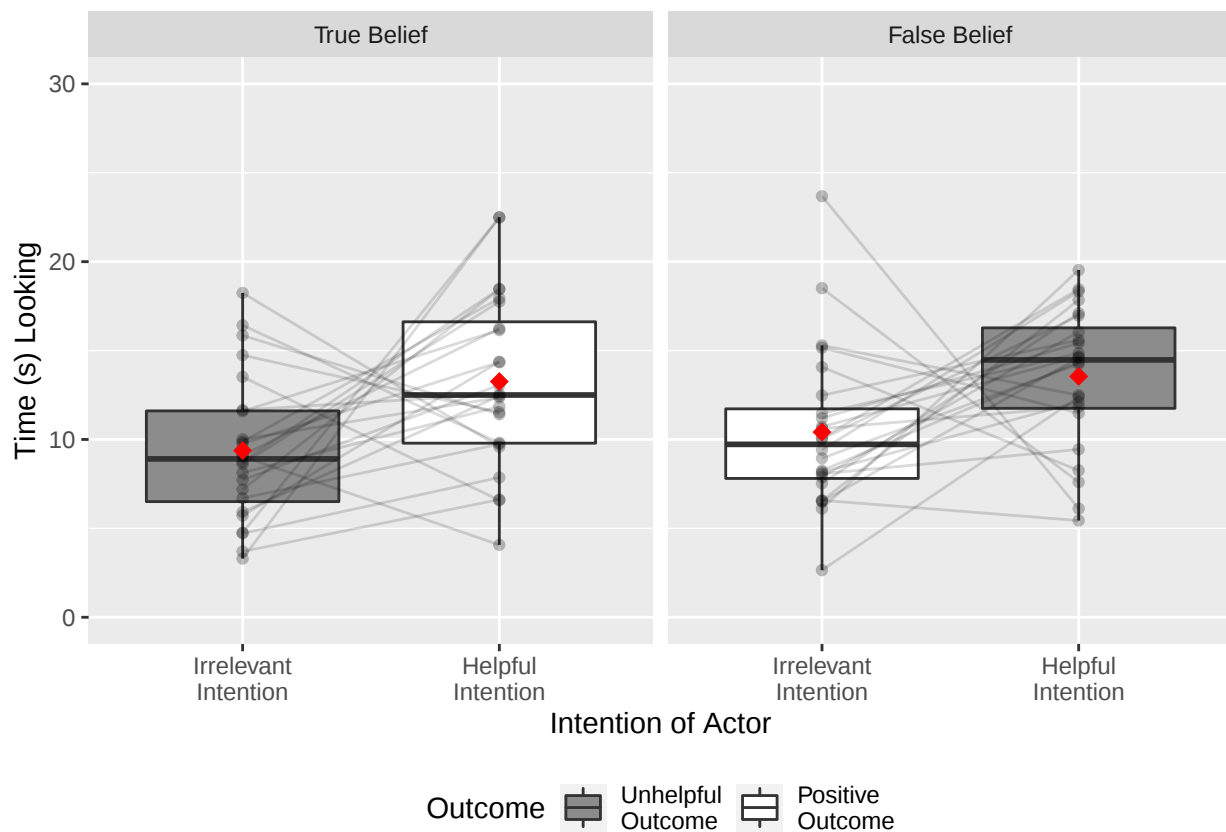
```
for (i in 1:nrow(bh2zoomL)) {
  if (bh2zoomL$Condition[i] == "True Belief") {
    if (bh2zoomL$Outcome[i] == "Unhelpful\nOutcome") {
      bh2zoomL$Intention[i] <- "Irrelevant\nIntention"
    }
    else if (bh2zoomL$Outcome[i] == "Positive\nOutcome") {
      bh2zoomL$Intention[i] <- "Helpful\nIntention"
    }
  }
}
```

```

    }
  }
  else if (bh2zoomL$Condition[i] == "False Belief") {
    if (bh2zoomL$Outcome[i] == "Positive\nOutcome") {
      bh2zoomL$Intention[i] <- "Irrelevant\nIntention"
    }
    else if (bh2zoomL$Outcome[i] == "Unhelpful\nOutcome") {
      bh2zoomL$Intention[i] <- "Helpful\nIntention"
    }
  }
}
bh2zoomL$Intention <- as.factor(bh2zoomL$Intention)
bh2zoomL$Intention <- relevel(bh2zoomL$Intention, "Irrelevant\nIntention")

ggplot(data = dplyr::filter(bh2zoomL), aes(x = Intention, y = LT, fill = Outcome)) +
  geom_boxplot(outlier.shape = NA) +
  facet_grid(~Condition) +
  geom_point(alpha = 0.25, show.legend = F) +
  geom_line(aes(group = Subject.ID), alpha = .15, linetype = 1) +
  stat_summary(fun = mean, geom = "point", size = 3, color = "red", shape = 18, show.legend = F) +
  theme(legend.position = "bottom") +
  scale_fill_manual(values = c("grey55", "grey100")) +
  ylab("Time (s) Looking") + xlab("Intention of Actor") + ylim(0, 30) # Figure 2B

```



```
# one sample t-test (proportionate looking)
## pref for Irrelevant-Intention vs. Positive-Intention (main text)
by(bh2zoom$pHelpfullI, bh2zoom$Condition, t.test, mu = 0.5, alternative = "two.sided")
```

```
## bh2zoom$Condition: False Belief
##
## One Sample t-test
##
## data: dd[x, ]
## t = 2.3658, df = 23, p-value = 0.0268
## alternative hypothesis: true mean is not equal to 0.5
## 95 percent confidence interval:
## 0.5088866 0.6326121
## sample estimates:
## mean of x
## 0.5707493
## -----
## bh2zoom$Condition: True Belief
##
## One Sample t-test
##
## data: dd[x, ]
## t = 2.7197, df = 23, p-value = 0.01222
## alternative hypothesis: true mean is not equal to 0.5
## 95 percent confidence interval:
## 0.5198361 0.6458888
## sample estimates:
## mean of x
## 0.5828624
```

```
by(bh2zoom$pHelpfullI, bh2zoom$Condition, lsr::cohensD, mu = 0.5)
```

```
## bh2zoom$Condition: False Belief
## [1] 0.482921
## -----
## bh2zoom$Condition: True Belief
## [1] 0.5551601
```

```
# two sample t-test: Difference in proportionate looking based on outcome, by condition (main text)
t.test(pPositive0 ~ Condition, data = bh2zoom, alternative = "two.sided")
```

```
##
## Welch Two Sample t-test
##
## data: pPositive0 by Condition
## t = -3.5982, df = 45.984, p-value = 0.0007807
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
## -0.23954580 -0.06767772
## sample estimates:
## mean in group False Belief mean in group True Belief
## 0.4292507 0.5828624
```

```
twosamplet.outcome <- t.test(pPositive0 ~ Condition, data = bh2zoom, alternative = "two.sided")
twosampled.outcome <- effsize::cohen.d(pPositive0 ~ Condition, data = bh2zoom)$estimate
```

Leonard Data Analysis

Data reading.

```
leonard_data <- read_csv("data/leonard_data.csv") %>%
  filter(include == 1) %>%
  mutate(version = recode(version, "in_person" = "In-Person", "online" = "Online"))
```

```
## Parsed with column specification:
## cols(
##   subject = col_character(),
##   date = col_character(),
##   gender = col_character(),
##   age_months = col_double(),
##   age = col_double(),
##   version = col_character(),
##   practice = col_double(),
##   test_question = col_double(),
##   inclusion_q = col_character(),
##   include = col_double(),
##   exclude_reason = col_character()
## )
```

```
#split data into in person and online versions
leonard_inperson <- filter(leonard_data, version == "In-Person")
leonard_online <- filter(leonard_data, version == "Online")
```

In person results

```
#are children above chance at critical question?
model<-binom.test(sum(leonard_inperson$test_question),20,p=.5)
model #significant
```

```
##
## Exact binomial test
##
## data: sum(leonard_inperson$test_question) and 20
## number of successes = 18, number of trials = 20, p-value = 0.0004025
## alternative hypothesis: true probability of success is not equal to 0.5
## 95 percent confidence interval:
##  0.6830173 0.9876515
## sample estimates:
## probability of success
##                0.9
```

```
#get bootstrapped CI
ProportionFunction<-function(data,indices){return(sum(data[indices])/length(data[indices]))}
table(leonard_inperson$test_question)
```

```
##
## 0 1
## 2 18
```

```
##95% ci
exp1<-c(rep(1,18),rep(0,2))
resultsexp1 <- boot::boot(data=exp1, statistic=ProportionFunction, R=500000)
boot::boot.ci(resultsexp1,type="basic")
```

```
## BOOTSTRAP CONFIDENCE INTERVAL CALCULATIONS
## Based on 500000 bootstrap replicates
##
## CALL :
## boot::boot.ci(boot.out = resultsexp1, type = "basic")
##
## Intervals :
## Level      Basic
## 95%      ( 0.80,  1.05 )
## Calculations and Intervals on Original Scale
```

```
##included children who got "which tower was better" question wrong
d <- filter(leonard_data, version == "In-Person" & exclude_reason != "practice")

#are children above chance at critical question?
model <- binom.test(sum(d$test_question),27,p=.5)
model
```

```
##
## Exact binomial test
##
## data: sum(d$test_question) and 27
## number of successes = 0, number of trials = 27, p-value = 1.49e-08
## alternative hypothesis: true probability of success is not equal to 0.5
## 95 percent confidence interval:
## 0.0000000 0.1277029
## sample estimates:
## probability of success
## 0
```

```
##95% ci
table(d$test_question)
```

```
## < table of extent 0 >
```

```
exp1<-c(rep(1,20),rep(0,7))
resultsexp1 <- boot(data=exp1, statistic=ProportionFunction, R=50000)
boot.ci(resultsexp1,type="basic")
```

```
## BOOTSTRAP CONFIDENCE INTERVAL CALCULATIONS
## Based on 50000 bootstrap replicates
##
## CALL :
## boot.ci(boot.out = resultsexp1, type = "basic")
##
## Intervals :
## Level      Basic
## 95%      ( 0.5926,  0.9259 )
## Calculations and Intervals on Original Scale
```

Online results

```
#are children above chance at critical question?
model<-binom.test(sum(leonard_online$test_question),20,p=.5)
model #significant
```

```
##
## Exact binomial test
##
## data: sum(leonard_online$test_question) and 20
## number of successes = 17, number of trials = 20, p-value = 0.002577
## alternative hypothesis: true probability of success is not equal to 0.5
## 95 percent confidence interval:
##  0.6210732 0.9679291
## sample estimates:
## probability of success
##                0.85
```

```
#get bootstrapped CI
ProportionFunction<-function(data,indices){return(sum(data[indices])/length(data[indices]))}
table(leonard_online$test_question)
```

```
##
##  0  1
##  3 17
```

```
##95% ci
exp1<-c(rep(1,17),rep(0,3))
resultsexp1 <- boot::boot(data=exp1, statistic=ProportionFunction, R=50000)
boot::boot.ci(resultsexp1,type="basic")
```

```
## BOOTSTRAP CONFIDENCE INTERVAL CALCULATIONS
## Based on 50000 bootstrap replicates
##
## CALL :
## boot::boot.ci(boot.out = resultsexp1, type = "basic")
##
## Intervals :
## Level      Basic
## 95%      ( 0.7,  1.0 )
## Calculations and Intervals on Original Scale
```

Asaba Wu Data Analysis

Data reading.

```
asaba_data = read_csv("data/asaba_wu_data.csv")
```

```
## Warning: Missing column names filled in: 'X1' [1]
```

```
## Parsed with column specification:
## cols(
##   X1 = col_double(),
##   id = col_character(),
##   location = col_character(),
##   age = col_double(),
##   activity = col_character(),
##   outcome = col_character(),
##   question = col_character(),
##   chose_surprise = col_double(),
##   correct = col_double()
## )
```

```
asaba_data = asaba_data %>%
  mutate(location = recode(location, "in-person" = "In-Person",
                             "online" = "Online")) %>%
  mutate(outcome = recode(outcome, "fail" = "Fail",
                             "success" = "Success"))
emo_inperson = asaba_data %>%
  filter(location == "In-Person") %>%
  filter(age > 5.99)
emo_online = filter(asaba_data, location == "Online")
```

In person

```
inperson_glm = glmer(chose_surprise ~ outcome * age + activity + (1|id),
                     data = emo_inperson, family = "binomial")
```

```
## Warning in checkConv(attr(opt, "derivs"), opt$par, ctrl = control$checkConv, :
## Model failed to converge with max|grad| = 0.0420008 (tol = 0.001, component 1)
```

```
summary(inperson_glm)
```

```
## Generalized linear mixed model fit by maximum likelihood (Laplace
## Approximation) [glmerMod]
## Family: binomial ( logit )
## Formula: chose_surprise ~ outcome * age + activity + (1 | id)
## Data: emo_inperson
##
##      AIC      BIC   logLik deviance df.resid
##    64.5    86.3   -24.3    48.5      104
```

```
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -1.6451 -0.0937 -0.0372  0.1153 15.2453
##
## Random effects:
##   Groups Name      Variance Std.Dev.
##   id      (Intercept) 3.588    1.894
## Number of obs: 112, groups: id, 14
##
## Fixed effects:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)   -14.9529     7.7463  -1.930   0.0536 .
## outcomeSuccess    13.1479     9.4011   1.399   0.1619
## age              2.2839     1.0471   2.181   0.0292 *
## activitymath     -0.7210     1.2175  -0.592   0.5537
## activityspelling  -1.4221     1.2541  -1.134   0.2568
## activitythrow    -0.7181     1.2174  -0.590   0.5553
## outcomeSuccess:age -2.6440     1.2978  -2.037   0.0416 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##              (Intr) otcmSc age    actvtym actvtys actvtyt
## outcomScscs -0.501
## age          -0.989  0.514
## activitymth  -0.013 -0.027 -0.074
## actvtysplln  0.071 -0.067 -0.164  0.528
## actvtythrw  -0.014 -0.027 -0.073  0.517  0.528
## otcmScscs:g  0.539 -0.987 -0.562  0.054  0.114  0.054
## convergence code: 0
## Model failed to converge with max|grad| = 0.0420008 (tol = 0.001, component 1)
```

Online

```
online_glm = glmer(chose_surprise ~ outcome * age + activity + (1|id),
                  data = emo_online, family = "binomial")
summary(online_glm)
```

```
## Generalized linear mixed model fit by maximum likelihood (Laplace
##   Approximation) [glmerMod]
##   Family: binomial ( logit )
## Formula: chose_surprise ~ outcome * age + activity + (1 | id)
##   Data: emo_online
##
##      AIC      BIC    logLik deviance df.resid
##    351.0    382.1   -167.5    335.0     352
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -12.6094  -0.3598  0.0973  0.3308  3.0009
##
```

```
## Random effects:
##   Groups Name      Variance Std.Dev.
##   id      (Intercept) 4.578    2.14
## Number of obs: 360, groups: id, 90
##
## Fixed effects:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)   -2.147e+00  3.092e+00  -0.694  0.48747
## outcomeSuccess  4.454e+00  3.210e+00   1.387  0.16533
## age           7.051e-01  4.122e-01   1.711  0.08716 .
## activitymath   -2.312e-05  4.430e-01   0.000  0.99996
## activityspelling -7.186e-01  5.045e-01  -1.424  0.15431
## activitythrow  -3.905e-01  5.014e-01  -0.779  0.43606
## outcomeSuccess:age -1.157e+00  4.386e-01  -2.638  0.00834 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##              (Intr) otcmSc age      actvtym actvtys actvtyt
## outcomScss -0.616
## age        -0.983  0.628
## activitymth -0.072  0.000  0.000
## actvtysplln -0.079 -0.029 -0.024  0.439
## actvtythrw -0.083 -0.020 -0.011  0.442  0.564
## otcmScss:g  0.601 -0.985 -0.635  0.000  0.067  0.047
```

Meta Analysis

Effect size computation

Leonard data: binomial test (choice) + 95% CI. Will run binomial tests on both online and in person experiments

```
#unified model
leonard_mod <- glm(test_question ~ version,
                  data = leonard_data)

# convert odds ratio to d
leonard_diff_es <- logoddsratio_to_d(leonard_mod[1]$coefficients[2])

#in person model
leonard_test_inperson <- binom.test(sum(leonard_inperson$test_question),20,p=.5)

leonard_es_inperson <- effectsize::oddsratio_to_d(mean(leonard_inperson$test_question)/(1+mean(leonard_inperson$test_question)),
                                                mean(leonard_online$test_question)/(1+mean(leonard_online$test_question)))

leonard_es_online <- effectsize::oddsratio_to_d(mean(leonard_online$test_question)/(1+mean(leonard_online$test_question)),
                                                mean(leonard_inperson$test_question)/(1+mean(leonard_inperson$test_question)))

leonard_ma <- tribble(~experiment, ~context, ~n, ~es, ~var,
                    "Study 1", "In-Person",
                    length(leonard_inperson$test_question), leonard_es_inperson,
                    compute.es::des(d=leonard_es_inperson, n.1 = 10, n.2 = 10)$var.d,
                    "Study 1", "Online",
```

```
length(leonard_online$test_question), leonard_es_online,
compute.es::des(d=leonard_es_online, n.1 = 10, n.2 = 10)$var.d)
```

```
## Mean Differences ES:
##
## d [ 95 %CI] = 1.21 [ 0.26 , 2.16 ]
##   var(d) = 0.24
##   p-value(d) = 0.02
##   U3(d) = 88.71 %
##   CLES(d) = 80.42 %
##   Cliff's Delta = 0.61
##
## g [ 95 %CI] = 1.16 [ 0.25 , 2.07 ]
##   var(g) = 0.22
##   p-value(g) = 0.02
##   U3(g) = 87.7 %
##   CLES(g) = 79.4 %
##
## Correlation ES:
##
## r [ 95 %CI] = 0.52 [ 0.1 , 0.78 ]
##   var(r) = 0.02
##   p-value(r) = 0.03
##
## z [ 95 %CI] = 0.57 [ 0.1 , 1.05 ]
##   var(z) = 0.06
##   p-value(z) = 0.03
##
## Odds Ratio ES:
##
## OR [ 95 %CI] = 9 [ 1.6 , 50.74 ]
##   p-value(OR) = 0.02
##
## Log OR [ 95 %CI] = 2.2 [ 0.47 , 3.93 ]
##   var(lOR) = 0.78
##   p-value(Log OR) = 0.02
##
## Other:
##
## NNT = 2.25
## Total N = 20
##
## Mean Differences ES:
##
## d [ 95 %CI] = 0.96 [ 0.03 , 1.88 ]
##   var(d) = 0.22
##   p-value(d) = 0.06
##   U3(d) = 83.05 %
##   CLES(d) = 75.06 %
##   Cliff's Delta = 0.5
##
## g [ 95 %CI] = 0.92 [ 0.03 , 1.8 ]
##   var(g) = 0.2
##   p-value(g) = 0.06
##   U3(g) = 82.01 %
```

```
## CLES(g) = 74.14 %
##
## Correlation ES:
##
## r [ 95 %CI] = 0.43 [ -0.01 , 0.73 ]
## var(r) = 0.03
## p-value(r) = 0.07
##
## z [ 95 %CI] = 0.46 [ -0.01 , 0.94 ]
## var(z) = 0.06
## p-value(z) = 0.07
##
## Odds Ratio ES:
##
## OR [ 95 %CI] = 5.67 [ 1.06 , 30.35 ]
## p-value(OR) = 0.06
##
## Log OR [ 95 %CI] = 1.73 [ 0.06 , 3.41 ]
## var(lOR) = 0.73
## p-value(Log OR) = 0.06
##
## Other:
##
## NNT = 2.89
## Total N = 20
```

Asaba Wu data: mixed effects logistic regression (choice), outcome was main variable of interest + age (and interaction). Will keep this analysis for both studies. Effect size (d) for each fixed effect was derived via EMAtools package

```
asaba_data$age.c <- scale(asaba_data$age, center = TRUE, scale = FALSE)
#combined model
asaba_mod <- glmer(chose_surprise ~ outcome * age.c * location +
                  + (1|id),
                  family = "binomial", data = asaba_data)
```

```
## Warning in checkConv(attr(opt, "derivs"), opt$par, ctrl = control$checkConv, :
## Model failed to converge with max|grad| = 0.00193749 (tol = 0.001, component 1)
```

```
#in person model
asaba_test_inperson <- glmer(chose_surprise ~ outcome * age.c + (1|id),
                             family = "binomial", data = asaba_data %>% filter(location == "In-Person"))
#online model
asaba_test_online <- glmer(chose_surprise ~ outcome * age.c + (1|id),
                           family = "binomial", data = asaba_data %>% filter(location == "Online"))

#effect sizes of in person model
asaba_es_inperson = lme.dscore(asaba_test_inperson,
                               data=asaba_data %>% filter(location == "In-Person"),
                               type="lme4")
#effect sizes of online moel
asaba_es_online = lme.dscore(asaba_test_online,
                              data=asaba_data %>% filter(location == "Online"),
```

```

                                type="lme4")

n_inperson <- length(unique(filter(asaba_data, location == "In-Person")$id))
n_online <- length(unique(filter(asaba_data, location == "Online")$id))

# note:ES are negative, so we reverse them
aw_ma <- tribble(~experiment, ~context, ~n, ~es, ~var,
                  "Study 2", "In-Person",
                  n_inperson,
                  -asaba_es_inperson$d[1],
                  compute.es::des(d=-asaba_es_inperson$d[1],
                                   n.1 = n_inperson/2, n.2 = n_inperson/2)$var.d,
                  "Study 2", "Online",
                  n_online, -asaba_es_online$d[1],
                  compute.es::des(d=-asaba_es_online$d[1],
                                   n.1 = n_online/2, n.2 = n_online/2)$var.d)

## Mean Differences ES:
##
## d [ 95 %CI] = 1.38 [ 0.56 , 2.21 ]
## var(d) = 0.18
## p-value(d) = 0
## U3(d) = 91.68 %
## CLES(d) = 83.61 %
## Cliff's Delta = 0.67
##
## g [ 95 %CI] = 1.34 [ 0.54 , 2.14 ]
## var(g) = 0.17
## p-value(g) = 0
## U3(g) = 91.04 %
## CLES(g) = 82.89 %
##
## Correlation ES:
##
## r [ 95 %CI] = 0.57 [ 0.25 , 0.78 ]
## var(r) = 0.01
## p-value(r) = 0
##
## z [ 95 %CI] = 0.65 [ 0.25 , 1.04 ]
## var(z) = 0.04
## p-value(z) = 0
##
## Odds Ratio ES:
##
## OR [ 95 %CI] = 12.3 [ 2.76 , 54.91 ]
## p-value(OR) = 0
##
## Log OR [ 95 %CI] = 2.51 [ 1.01 , 4.01 ]
## var(lOR) = 0.58
## p-value(Log OR) = 0
##
## Other:
##

```

```

## NNT = 1.98
## Total N = 28Mean Differences ES:
##
## d [ 95 %CI] = 1.47 [ 1 , 1.93 ]
## var(d) = 0.06
## p-value(d) = 0
## U3(d) = 92.88 %
## CLES(d) = 85.02 %
## Cliff's Delta = 0.7
##
## g [ 95 %CI] = 1.45 [ 0.99 , 1.92 ]
## var(g) = 0.06
## p-value(g) = 0
## U3(g) = 92.71 %
## CLES(g) = 84.82 %
##
## Correlation ES:
##
## r [ 95 %CI] = 0.59 [ 0.44 , 0.71 ]
## var(r) = 0
## p-value(r) = 0
##
## z [ 95 %CI] = 0.68 [ 0.47 , 0.89 ]
## var(z) = 0.01
## p-value(z) = 0
##
## Odds Ratio ES:
##
## OR [ 95 %CI] = 14.31 [ 6.15 , 33.3 ]
## p-value(OR) = 0
##
## Log OR [ 95 %CI] = 2.66 [ 1.82 , 3.51 ]
## var(logOR) = 0.19
## p-value(Log OR) = 0
##
## Other:
##
## NNT = 1.87
## Total N = 90

```

Woo Spelke data: for exp 1, binomial test (choice) for each condition, chi square for comparison between conditions; for exp 2, one sample t's for each condition, two sample t's for comparison between conditions. Will run binomial tests + two sample t's on both online + in person experiments.

```

values <- choice.dm$value
chi2 <- chisq.test(matrix(values, nrow=2))

woospelke1_es <- esc::esc_chisq(chisq = chi2$statistic, totaln = sum(values),
                              es.type = "d")

```

For exp2

```

bh2zoomL %>%
  group_by(Subject.ID, Condition) %>%
  summarise(LT_diff = LT[Outcome == "Positive\nOutcome"] - LT[Outcome == "Unhelpful\nOutcome"]) %>%
  group_by(Condition) %>%
  summarise(d = mean(LT_diff) / sd(LT_diff))

```

`summarise()` has grouped output by 'Subject.ID'. You can override using the `.groups` argument.

```

## # A tibble: 2 x 2
##   Condition      d
##   <fct>        <dbl>
## 1 True Belief  0.537
## 2 False Belief -0.432

```

```

woospelke2_mod <- lmer(LT ~ Condition * Outcome + (1 | Subject.ID),
  data = bh2zoomL)

```

boundary (singular) fit: see ?isSingular

```

woospelke2_es <- lme.dscore(woospelke2_mod, data = bh2zoomL, type = "lme4") %>%
  slice(3)

```

boundary (singular) fit: see ?isSingular

what's the right ES for this interaction term... derive from an ANOVA?

```

ws_ma <- tribble(~experiment, ~context, ~n, ~es, ~var,
  "Study 3", "In-Person",
  sum(choice.dm$value) , woospelke1_es$es, woospelke1_es$var,
  "Study 3", "Online", length(unique(bh2zoomL$Subject.ID)),
  -woospelke2_es$d[1], # have to flip sign on interaction
  compute.es::des(d=-woospelke2_es$d[1], n.1 = 24, n.2 = 24)$var.d)

```

```

## Mean Differences ES:
##
## d [ 95 %CI] = 0.82 [ 0.23 , 1.41 ]
##   var(d) = 0.09
##   p-value(d) = 0.01
##   U3(d) = 79.49 %
##   CLES(d) = 71.98 %
##   Cliff's Delta = 0.44
##
## g [ 95 %CI] = 0.81 [ 0.23 , 1.39 ]
##   var(g) = 0.09
##   p-value(g) = 0.01
##   U3(g) = 79.1 %
##   CLES(g) = 71.66 %
##
## Correlation ES:
##

```

```
## r [ 95 %CI] = 0.38 [ 0.11 , 0.6 ]
## var(r) = 0.01
## p-value(r) = 0.01
##
## z [ 95 %CI] = 0.4 [ 0.11 , 0.69 ]
## var(z) = 0.02
## p-value(z) = 0.01
##
## Odds Ratio ES:
##
## OR [ 95 %CI] = 4.45 [ 1.53 , 12.97 ]
## p-value(OR) = 0.01
##
## Log OR [ 95 %CI] = 1.49 [ 0.42 , 2.56 ]
## var(lOR) = 0.3
## p-value(Log OR) = 0.01
##
## Other:
##
## NNT = 3.42
## Total N = 48
```

Liu Spelke data: looking time by trial type, mixed effects linear model; effect size (d) of trial type was derived via EMAtools package

```
liu_test_inperson <- lmer(scale(loglook) ~ trialtype + (1|subj),
                           data = orig.avg)
liu_test_online <- lmer(scale(loglook) ~ trialtype + (1|subj),
                        data = online.avg %>% filter(subj != "P7-"))
liu_es_inperson <- lme.dscore(liu_test_inperson,
                             data=orig.avg,
                             type="lme4")
liu_es_online <- lme.dscore(liu_test_inperson,
                           data=online.avg %>% filter(subj != "P7-"),
                           type="lme4")

ls_ma <- tribble(~experiment, ~context, ~n, ~es, ~var,
                 "Study 4", "In-Person",
                 length(unique(orig.avg$subj)), liu_es_inperson$d[1],
                 compute.es::des(d=liu_es_inperson$d[1], n.1 = length(unique(orig.avg$subj))/2,
                                n.2 = length(unique(orig.avg$subj))/2)$var.d,
                 "Study 4", "Online",
                 length(unique(online.avg$subj)), liu_es_online$d[1],
                 compute.es::des(d=liu_es_online$d[1], n.1 = length(unique(online.avg$subj))/2,
                                n.2 = length(unique(online.avg$subj))/2)$var.d)
```

```
## Mean Differences ES:
##
## d [ 95 %CI] = 1.43 [ 0.45 , 2.41 ]
## var(d) = 0.25
## p-value(d) = 0.01
## U3(d) = 92.32 %
## CLES(d) = 84.35 %
```

```

##   Cliff's Delta = 0.69
##
##   g [ 95 %CI] = 1.37 [ 0.43 , 2.31 ]
##   var(g) = 0.23
##   p-value(g) = 0.01
##   U3(g) = 91.41 %
##   CLES(g) = 83.3 %
##
##   Correlation ES:
##
##   r [ 95 %CI] = 0.58 [ 0.19 , 0.81 ]
##   var(r) = 0.02
##   p-value(r) = 0.01
##
##   z [ 95 %CI] = 0.66 [ 0.19 , 1.14 ]
##   var(z) = 0.06
##   p-value(z) = 0.01
##
##   Odds Ratio ES:
##
##   OR [ 95 %CI] = 13.3 [ 2.24 , 78.93 ]
##   p-value(OR) = 0.01
##
##   Log OR [ 95 %CI] = 2.59 [ 0.81 , 4.37 ]
##   var(lOR) = 0.83
##   p-value(Log OR) = 0.01
##
##   Other:
##
##   NNT = 1.92
##   Total N = 20
##   Mean Differences ES:
##
##   d [ 95 %CI] = 1.09 [ 0.28 , 1.9 ]
##   var(d) = 0.17
##   p-value(d) = 0.01
##   U3(d) = 86.17 %
##   CLES(d) = 77.91 %
##   Cliff's Delta = 0.56
##
##   g [ 95 %CI] = 1.05 [ 0.27 , 1.84 ]
##   var(g) = 0.16
##   p-value(g) = 0.01
##   U3(g) = 85.43 %
##   CLES(g) = 77.22 %
##
##   Correlation ES:
##
##   r [ 95 %CI] = 0.48 [ 0.12 , 0.73 ]
##   var(r) = 0.02
##   p-value(r) = 0.02
##
##   z [ 95 %CI] = 0.52 [ 0.12 , 0.92 ]
##   var(z) = 0.04
##   p-value(z) = 0.02

```

```
##
## Odds Ratio ES:
##
## OR [ 95 %CI] = 7.19 [ 1.66 , 31.17 ]
## p-value(OR) = 0.01
##
## Log OR [ 95 %CI] = 1.97 [ 0.51 , 3.44 ]
## var(lOR) = 0.56
## p-value(Log OR) = 0.01
##
## Other:
##
## NNT = 2.52
## Total N = 27
```

Meta-analysis

Get everything into a tibble.

```
ma_data <- bind_rows(leonard_ma, aw_ma, ws_ma, ls_ma)
ma_data
```

```
## # A tibble: 8 x 5
##   experiment context      n    es  var
##   <chr>      <chr>    <dbl> <dbl> <dbl>
## 1 Study 1    In-Person    20 1.21  0.24
## 2 Study 1    Online       20 0.956 0.22
## 3 Study 2    In-Person    28 1.38  0.18
## 4 Study 2    Online       90 1.47  0.06
## 5 Study 3    In-Person    46 1.22  0.119
## 6 Study 3    Online       48 0.823 0.09
## 7 Study 4    In-Person    20 1.43  0.25
## 8 Study 4    Online       27 1.09  0.17
```

Our approach is random-effects meta-regression with study-wise grouping. We're going to weight by N instead of ES variance because of the differences in ES.

```
# escalc(yi = es, ni = n, data = ma_data)

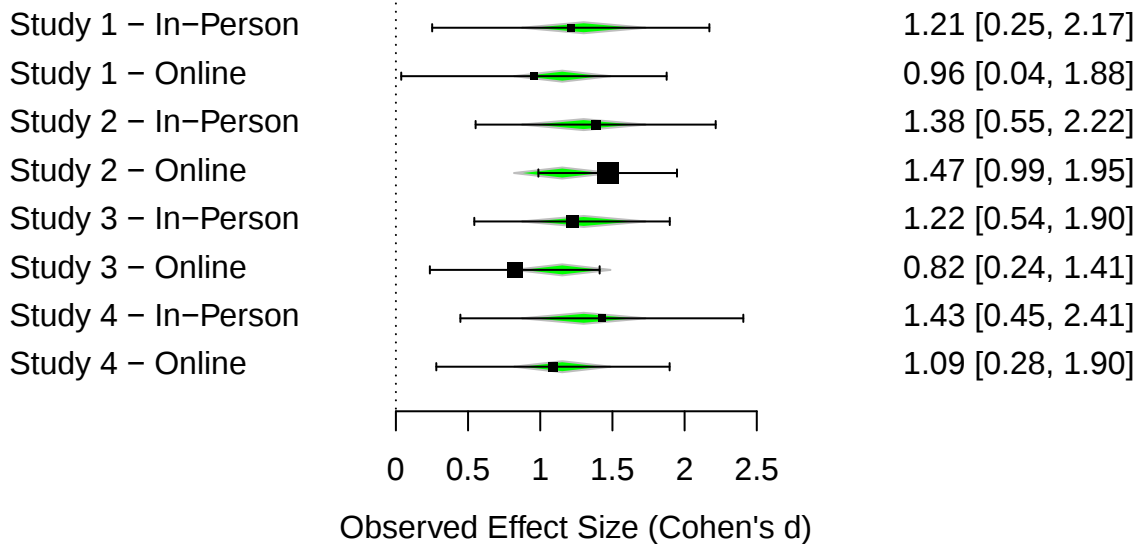
ma_mod <- rma.mv(yi = es, V = var, random = ~ 1 | experiment,
               mods = ~ context, slab = experiment, data = ma_data)
summary(ma_mod)
```

```
##
## Multivariate Meta-Analysis Model (k = 8; method: REML)
##
##   logLik Deviance      AIC      BIC      AICc
## -1.5149   3.0298   9.0298   8.4051   21.0298
##
## Variance Components:
##
##           estim      sqrt nlvls fixed      factor
```

```
## sigma^2    0.0096  0.0979      4    no  experiment
##
## Test for Residual Heterogeneity:
## QE(df = 6) = 3.2404, p-val = 0.7781
##
## Test of Moderators (coefficient 2):
## QM(df = 1) = 0.3068, p-val = 0.5796
##
## Model Results:
##
##              estimate      se      zval      pval      ci.lb      ci.ub
## intrcpt           1.3009  0.2188   5.9469 <.0001   0.8722  1.7296 ***
## contextOnline    -0.1484  0.2680  -0.5539  0.5796  -0.6736  0.3768
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Forest plot.

```
lt = c("Study 1 - In-Person", "Study 1 - Online", "Study 2 - In-Person", "Study 2 - Online", "Study 3 - In-Person", "Study 3 - Online", "Study 4 - In-Person", "Study 4 - Online")
ma_mod %>%
  forest(slab = lt, col = "green", xlab = "Observed Effect Size (Cohen's d)")
```



Graphing

Liu Spelke Data Prep

```
liu_graphing <- final.repl.data.avg %>%
  filter(trialtype != "famhab") %>%
  group_by(sample, trialtype) %>%
  summarise(looking_time = mean(avg_look),
            sems = std.error(avg_look))
```

`summarise()` has grouped output by 'sample'. You can override using the `.groups` argument.

Woo Spelke Data Prep

```
woo_study1_graphing <- choice.dm %>%
  mutate(Intention = recode(intention, "Irrelevant\nIntention" = "Irrelevant", "Helpful\nIntention" = "Helpful"),
  mutate(Outcome = recode(outcome, "Unhelpful\nOutcome" = "Unhelpful", "Positive\nOutcome" = "Helpful"))
woo_study2 <- dplyr::filter(bh2zoomL) %>%
  mutate(Outcome = recode(Outcome, "Unhelpful\nOutcome" = "Unhelpful", "Positive\nOutcome" = "Helpful"),
  mutate(Intention = recode(Intention, "Irrelevant\nIntention" = "Irrelevant", "Helpful\nIntention" = "Helpful"))
woo_study2
```

##	Relabeled.Script	Script	Subject.ID	Sex	Age...Month	Age...Day	Age.Decimal
## 1	1b	9	p25	F	15	9	15.30000
## 2	2b	10	p17	F	15	0	15.00000
## 3	3b	5	p26	F	14	10	14.33333
## 4	4b	14	p13	F	15	11	15.36667
## 5	5b	3	p22	M	14	18	14.60000
## 6	6b	12	p15	M	14	25	14.83333
## 7	7b	16	p19	M	14	28	14.93333
## 8	8b	7	p10	F	15	3	15.10000
## 9	9b	1	p9	F	15	9	15.30000
## 10	10b	2	p12	F	15	17	15.56667
## 11	11b	11	p23	M	14	24	14.80000
## 12	12b	4	p14	M	14	27	14.90000
## 13	13b	6	p18	F	14	24	14.80000
## 14	14b	8	p21	F	14	18	14.60000
## 15	15b	13	p24	F	14	20	14.66667
## 16	16b	15	p19.2	M	14	21	14.70000
## 17	1c	7	p43	M	14	12	14.40000
## 18	2c	9	p27	M	14	19	14.63333
## 19	3c	8	p32	F	15	19	15.63333
## 20	4c	2	p35	F	14	27	14.90000
## 21	5c	3	p29	F	14	18	14.60000
## 22	6c	1	p36	M	15	13	15.43333
## 23	7c	13	p34	M	15	4	15.13333
## 24	8c	11	p28	F	14	19	14.63333
## 25	9c	10	p44	M	15	20	15.66667
## 26	10c	4	p37	M	14	14	14.46667
## 27	11c	12	p42	F	14	21	14.70000
## 28	12c	14	p31	M	15	0	15.00000
## 29	13c	6	p41	F	14	19	14.63333
## 30	14c	5	p30	F	14	28	14.93333
## 31	15c	16	p33	F	15	13	15.43333
## 32	16c	15	p39	F	14	11	14.36667
## 33	1d	14	p62	F	14	11	14.36667
## 34	2d	15	p50	M	14	23	14.76667
## 35	3d	1	p56	F	15	1	15.03333
## 36	4d	5	p58	M	14	19	14.63333
## 37	5d	2	p49	F	14	29	14.96667
## 38	6d	16	p40	M	14	21	14.70000
## 39	7d	4	p51	F	14	29	14.96667

## 40	8d	10	p48	F	14	27	14.90000
## 41	9d	12	p45	M	14	15	14.50000
## 42	10d	11	p52	M	15	7	15.23333
## 43	11d	13	p59	M	14	15	14.50000
## 44	12d	3	p57	M	15	2	15.06667
## 45	13d	9	p53	F	15	2	15.06667
## 46	14d	8	p47	F	14	10	14.33333
## 47	16d	6	p61	M	15	20	15.66667
## 48	15d	3	p55	M	15	13	15.43333
## 49	1b	9	p25	F	15	9	15.30000
## 50	2b	10	p17	F	15	0	15.00000
## 51	3b	5	p26	F	14	10	14.33333
## 52	4b	14	p13	F	15	11	15.36667
## 53	5b	3	p22	M	14	18	14.60000
## 54	6b	12	p15	M	14	25	14.83333
## 55	7b	16	p19	M	14	28	14.93333
## 56	8b	7	p10	F	15	3	15.10000
## 57	9b	1	p9	F	15	9	15.30000
## 58	10b	2	p12	F	15	17	15.56667
## 59	11b	11	p23	M	14	24	14.80000
## 60	12b	4	p14	M	14	27	14.90000
## 61	13b	6	p18	F	14	24	14.80000
## 62	14b	8	p21	F	14	18	14.60000
## 63	15b	13	p24	F	14	20	14.66667
## 64	16b	15	p19.2	M	14	21	14.70000
## 65	1c	7	p43	M	14	12	14.40000
## 66	2c	9	p27	M	14	19	14.63333
## 67	3c	8	p32	F	15	19	15.63333
## 68	4c	2	p35	F	14	27	14.90000
## 69	5c	3	p29	F	14	18	14.60000
## 70	6c	1	p36	M	15	13	15.43333
## 71	7c	13	p34	M	15	4	15.13333
## 72	8c	11	p28	F	14	19	14.63333
## 73	9c	10	p44	M	15	20	15.66667
## 74	10c	4	p37	M	14	14	14.46667
## 75	11c	12	p42	F	14	21	14.70000
## 76	12c	14	p31	M	15	0	15.00000
## 77	13c	6	p41	F	14	19	14.63333
## 78	14c	5	p30	F	14	28	14.93333
## 79	15c	16	p33	F	15	13	15.43333
## 80	16c	15	p39	F	14	11	14.36667
## 81	1d	14	p62	F	14	11	14.36667
## 82	2d	15	p50	M	14	23	14.76667
## 83	3d	1	p56	F	15	1	15.03333
## 84	4d	5	p58	M	14	19	14.63333
## 85	5d	2	p49	F	14	29	14.96667
## 86	6d	16	p40	M	14	21	14.70000
## 87	7d	4	p51	F	14	29	14.96667
## 88	8d	10	p48	F	14	27	14.90000
## 89	9d	12	p45	M	14	15	14.50000
## 90	10d	11	p52	M	15	7	15.23333
## 91	11d	13	p59	M	14	15	14.50000
## 92	12d	3	p57	M	15	2	15.06667
## 93	13d	9	p53	F	15	2	15.06667

## 94	14d	8	p47	F	14	10	14.33333
## 95	16d	6	p61	M	15	20	15.66667
## 96	15d	3	p55	M	15	13	15.43333
##	Condition	Fam.Box.Color	Pink.Actor.Show.Side		Pink.Actor.Order		
## 1	False Belief	Blue	Left		1		
## 2	False Belief	Blue	Left		1		
## 3	True Belief	Green	Left		2		
## 4	False Belief	Green	Left		2		
## 5	True Belief	Blue	Right		2		
## 6	False Belief	Blue	Right		2		
## 7	False Belief	Green	Right		1		
## 8	True Belief	Green	Right		1		
## 9	True Belief	Blue	Left		1		
## 10	True Belief	Blue	Left		1		
## 11	False Belief	Blue	Right		2		
## 12	True Belief	Blue	Right		2		
## 13	True Belief	Green	Left		2		
## 14	True Belief	Green	Right		1		
## 15	False Belief	Green	Left		2		
## 16	False Belief	Green	Right		1		
## 17	True Belief	Green	Right		1		
## 18	False Belief	Blue	Left		1		
## 19	True Belief	Green	Right		1		
## 20	True Belief	Blue	Left		1		
## 21	True Belief	Blue	Right		2		
## 22	True Belief	Blue	Left		1		
## 23	False Belief	Green	Left		2		
## 24	False Belief	Blue	Right		2		
## 25	False Belief	Blue	Left		1		
## 26	True Belief	Blue	Right		2		
## 27	False Belief	Blue	Right		2		
## 28	False Belief	Green	Left		2		
## 29	True Belief	Green	Left		2		
## 30	True Belief	Green	Left		2		
## 31	False Belief	Green	Right		1		
## 32	False Belief	Green	Right		1		
## 33	False Belief	Green	Left		2		
## 34	False Belief	Green	Right		1		
## 35	True Belief	Blue	Left		1		
## 36	True Belief	Green	Left		2		
## 37	True Belief	Blue	Left		1		
## 38	False Belief	Green	Right		1		
## 39	True Belief	Blue	Right		2		
## 40	False Belief	Blue	Left		1		
## 41	False Belief	Blue	Right		2		
## 42	False Belief	Blue	Right		2		
## 43	False Belief	Green	Left		2		
## 44	True Belief	Blue	Right		2		
## 45	False Belief	Blue	Left		1		
## 46	True Belief	Green	Right		1		
## 47	True Belief	Green	Left		2		
## 48	True Belief	Green	Right		1		
## 49	False Belief	Blue	Left		1		
## 50	False Belief	Blue	Left		1		

## 51	True Belief	Green	Left	2	
## 52	False Belief	Green	Left	2	
## 53	True Belief	Blue	Right	2	
## 54	False Belief	Blue	Right	2	
## 55	False Belief	Green	Right	1	
## 56	True Belief	Green	Right	1	
## 57	True Belief	Blue	Left	1	
## 58	True Belief	Blue	Left	1	
## 59	False Belief	Blue	Right	2	
## 60	True Belief	Blue	Right	2	
## 61	True Belief	Green	Left	2	
## 62	True Belief	Green	Right	1	
## 63	False Belief	Green	Left	2	
## 64	False Belief	Green	Right	1	
## 65	True Belief	Green	Right	1	
## 66	False Belief	Blue	Left	1	
## 67	True Belief	Green	Right	1	
## 68	True Belief	Blue	Left	1	
## 69	True Belief	Blue	Right	2	
## 70	True Belief	Blue	Left	1	
## 71	False Belief	Green	Left	2	
## 72	False Belief	Blue	Right	2	
## 73	False Belief	Blue	Left	1	
## 74	True Belief	Blue	Right	2	
## 75	False Belief	Blue	Right	2	
## 76	False Belief	Green	Left	2	
## 77	True Belief	Green	Left	2	
## 78	True Belief	Green	Left	2	
## 79	False Belief	Green	Right	1	
## 80	False Belief	Green	Right	1	
## 81	False Belief	Green	Left	2	
## 82	False Belief	Green	Right	1	
## 83	True Belief	Blue	Left	1	
## 84	True Belief	Green	Left	2	
## 85	True Belief	Blue	Left	1	
## 86	False Belief	Green	Right	1	
## 87	True Belief	Blue	Right	2	
## 88	False Belief	Blue	Left	1	
## 89	False Belief	Blue	Right	2	
## 90	False Belief	Blue	Right	2	
## 91	False Belief	Green	Left	2	
## 92	True Belief	Blue	Right	2	
## 93	False Belief	Blue	Left	1	
## 94	True Belief	Green	Right	1	
## 95	True Belief	Green	Left	2	
## 96	True Belief	Green	Right	1	
##	Test.Actor.Old.Toy.Color	Pink	Actor.Choice.Side	ChoiceLeft	ChoiceRight
## 1		Pink	Left	15.29	12.49
## 2		Yellow	Left	7.60	18.51
## 3		Yellow	Left	9.87	17.94
## 4		Pink	Left	10.61	11.84
## 5		Pink	Right	11.66	12.55
## 6		Yellow	Right	10.03	16.96
## 7		Pink	Right	14.25	8.94

## 8	Yellow	Right	7.86	4.72
## 9	Pink	Left	18.44	7.19
## 10	Yellow	Left	3.30	22.50
## 11	Pink	Right	15.59	12.48
## 12	Yellow	Right	9.81	16.42
## 13	Pink	Left	11.42	15.85
## 14	Pink	Right	8.62	17.75
## 15	Yellow	Left	14.85	11.47
## 16	Yellow	Right	7.90	16.05
## 17	Yellow	Right	13.06	7.73
## 18	Pink	Left	8.25	14.36
## 19	Pink	Right	4.76	22.48
## 20	Yellow	Left	9.77	14.34
## 21	Pink	Right	8.13	11.85
## 22	Pink	Left	9.59	18.24
## 23	Yellow	Left	18.32	9.42
## 24	Pink	Right	18.45	10.09
## 25	Yellow	Left	12.38	2.65
## 26	Yellow	Right	16.15	11.59
## 27	Yellow	Right	8.07	9.44
## 28	Pink	Left	7.53	17.10
## 29	Pink	Left	11.53	14.74
## 30	Yellow	Left	8.76	18.47
## 31	Pink	Right	15.42	11.20
## 32	Yellow	Right	10.71	14.66
## 33	Pink	Left	6.50	14.59
## 34	Yellow	Right	8.16	12.12
## 35	Pink	Left	4.07	9.05
## 36	Yellow	Left	5.72	14.37
## 37	Yellow	Left	5.92	12.45
## 38	Pink	Right	11.48	15.16
## 39	Yellow	Right	6.58	13.52
## 40	Yellow	Left	17.84	6.55
## 41	Yellow	Right	6.58	5.44
## 42	Pink	Right	6.11	23.68
## 43	Yellow	Left	8.26	14.07
## 44	Pink	Right	10.01	12.36
## 45	Pink	Left	6.11	19.53
## 46	Pink	Right	6.70	9.74
## 47	Pink	Left	6.62	3.70
## 48	Yellow	Right	16.24	9.11
## 49	Pink	Left	15.29	12.49
## 50	Yellow	Left	7.60	18.51
## 51	Yellow	Left	9.87	17.94
## 52	Pink	Left	10.61	11.84
## 53	Pink	Right	11.66	12.55
## 54	Yellow	Right	10.03	16.96
## 55	Pink	Right	14.25	8.94
## 56	Yellow	Right	7.86	4.72
## 57	Pink	Left	18.44	7.19
## 58	Yellow	Left	3.30	22.50
## 59	Pink	Right	15.59	12.48
## 60	Yellow	Right	9.81	16.42
## 61	Pink	Left	11.42	15.85

## 62	Pink	Right	8.62	17.75		
## 63	Yellow	Left	14.85	11.47		
## 64	Yellow	Right	7.90	16.05		
## 65	Yellow	Right	13.06	7.73		
## 66	Pink	Left	8.25	14.36		
## 67	Pink	Right	4.76	22.48		
## 68	Yellow	Left	9.77	14.34		
## 69	Pink	Right	8.13	11.85		
## 70	Pink	Left	9.59	18.24		
## 71	Yellow	Left	18.32	9.42		
## 72	Pink	Right	18.45	10.09		
## 73	Yellow	Left	12.38	2.65		
## 74	Yellow	Right	16.15	11.59		
## 75	Yellow	Right	8.07	9.44		
## 76	Pink	Left	7.53	17.10		
## 77	Pink	Left	11.53	14.74		
## 78	Yellow	Left	8.76	18.47		
## 79	Pink	Right	15.42	11.20		
## 80	Yellow	Right	10.71	14.66		
## 81	Pink	Left	6.50	14.59		
## 82	Yellow	Right	8.16	12.12		
## 83	Pink	Left	4.07	9.05		
## 84	Yellow	Left	5.72	14.37		
## 85	Yellow	Left	5.92	12.45		
## 86	Pink	Right	11.48	15.16		
## 87	Yellow	Right	6.58	13.52		
## 88	Yellow	Left	17.84	6.55		
## 89	Yellow	Right	6.58	5.44		
## 90	Pink	Right	6.11	23.68		
## 91	Yellow	Left	8.26	14.07		
## 92	Pink	Right	10.01	12.36		
## 93	Pink	Left	6.11	19.53		
## 94	Pink	Right	6.70	9.74		
## 95	Pink	Left	6.62	3.70		
## 96	Yellow	Right	16.24	9.11		
##	pPositive0	pUnhelpful0	pIrrelevantI	pHelpfulI	ActorType	LT
## 1	0.5503960	0.4496040	0.5503960	0.4496040	Positive-Outcome	15.29
## 2	0.7089238	0.2910762	0.7089238	0.2910762	Positive-Outcome	18.51
## 3	0.6450917	0.3549083	0.3549083	0.6450917	Positive-Outcome	17.94
## 4	0.4726058	0.5273942	0.4726058	0.5273942	Positive-Outcome	10.61
## 5	0.5183808	0.4816192	0.4816192	0.5183808	Positive-Outcome	12.55
## 6	0.3716191	0.6283809	0.3716191	0.6283809	Positive-Outcome	10.03
## 7	0.3855110	0.6144890	0.3855110	0.6144890	Positive-Outcome	8.94
## 8	0.6248013	0.3751987	0.3751987	0.6248013	Positive-Outcome	7.86
## 9	0.7194694	0.2805306	0.2805306	0.7194694	Positive-Outcome	18.44
## 10	0.8720930	0.1279070	0.1279070	0.8720930	Positive-Outcome	22.50
## 11	0.4446028	0.5553972	0.4446028	0.5553972	Positive-Outcome	12.48
## 12	0.3739992	0.6260008	0.6260008	0.3739992	Positive-Outcome	9.81
## 13	0.4187752	0.5812248	0.5812248	0.4187752	Positive-Outcome	11.42
## 14	0.6731134	0.3268866	0.3268866	0.6731134	Positive-Outcome	17.75
## 15	0.4357903	0.5642097	0.4357903	0.5642097	Positive-Outcome	11.47
## 16	0.3298539	0.6701461	0.3298539	0.6701461	Positive-Outcome	7.90
## 17	0.6281866	0.3718134	0.3718134	0.6281866	Positive-Outcome	13.06
## 18	0.3648828	0.6351172	0.3648828	0.6351172	Positive-Outcome	8.25

## 19	0.8252570	0.1747430	0.1747430	0.8252570	Positive-Outcome	22.48
## 20	0.5947740	0.4052260	0.4052260	0.5947740	Positive-Outcome	14.34
## 21	0.5930931	0.4069069	0.4069069	0.5930931	Positive-Outcome	11.85
## 22	0.3445922	0.6554078	0.6554078	0.3445922	Positive-Outcome	9.59
## 23	0.3395818	0.6604182	0.3395818	0.6604182	Positive-Outcome	9.42
## 24	0.3535389	0.6464611	0.3535389	0.6464611	Positive-Outcome	10.09
## 25	0.1763140	0.8236860	0.1763140	0.8236860	Positive-Outcome	2.65
## 26	0.5821918	0.4178082	0.4178082	0.5821918	Positive-Outcome	16.15
## 27	0.4608795	0.5391205	0.4608795	0.5391205	Positive-Outcome	8.07
## 28	0.3057247	0.6942753	0.3057247	0.6942753	Positive-Outcome	7.53
## 29	0.4389037	0.5610963	0.5610963	0.4389037	Positive-Outcome	11.53
## 30	0.6782960	0.3217040	0.3217040	0.6782960	Positive-Outcome	18.47
## 31	0.4207363	0.5792637	0.4207363	0.5792637	Positive-Outcome	11.20
## 32	0.4221521	0.5778479	0.4221521	0.5778479	Positive-Outcome	10.71
## 33	0.3082029	0.6917971	0.3082029	0.6917971	Positive-Outcome	6.50
## 34	0.4023669	0.5976331	0.4023669	0.5976331	Positive-Outcome	8.16
## 35	0.3102134	0.6897866	0.6897866	0.3102134	Positive-Outcome	4.07
## 36	0.7152812	0.2847188	0.2847188	0.7152812	Positive-Outcome	14.37
## 37	0.6777354	0.3222646	0.3222646	0.6777354	Positive-Outcome	12.45
## 38	0.5690691	0.4309309	0.5690691	0.4309309	Positive-Outcome	15.16
## 39	0.3273632	0.6726368	0.6726368	0.3273632	Positive-Outcome	6.58
## 40	0.2685527	0.7314473	0.2685527	0.7314473	Positive-Outcome	6.55
## 41	0.5474210	0.4525790	0.5474210	0.4525790	Positive-Outcome	6.58
## 42	0.7948976	0.2051024	0.7948976	0.2051024	Positive-Outcome	23.68
## 43	0.6300940	0.3699060	0.6300940	0.3699060	Positive-Outcome	14.07
## 44	0.5525257	0.4474743	0.4474743	0.5525257	Positive-Outcome	12.36
## 45	0.2382995	0.7617005	0.2382995	0.7617005	Positive-Outcome	6.11
## 46	0.5924574	0.4075426	0.4075426	0.5924574	Positive-Outcome	9.74
## 47	0.6414729	0.3585271	0.3585271	0.6414729	Positive-Outcome	6.62
## 48	0.6406312	0.3593688	0.3593688	0.6406312	Positive-Outcome	16.24
## 49	0.5503960	0.4496040	0.5503960	0.4496040	Unhelpful-Outcome	12.49
## 50	0.7089238	0.2910762	0.7089238	0.2910762	Unhelpful-Outcome	7.60
## 51	0.6450917	0.3549083	0.3549083	0.6450917	Unhelpful-Outcome	9.87
## 52	0.4726058	0.5273942	0.4726058	0.5273942	Unhelpful-Outcome	11.84
## 53	0.5183808	0.4816192	0.4816192	0.5183808	Unhelpful-Outcome	11.66
## 54	0.3716191	0.6283809	0.3716191	0.6283809	Unhelpful-Outcome	16.96
## 55	0.3855110	0.6144890	0.3855110	0.6144890	Unhelpful-Outcome	14.25
## 56	0.6248013	0.3751987	0.3751987	0.6248013	Unhelpful-Outcome	4.72
## 57	0.7194694	0.2805306	0.2805306	0.7194694	Unhelpful-Outcome	7.19
## 58	0.8720930	0.1279070	0.1279070	0.8720930	Unhelpful-Outcome	3.30
## 59	0.4446028	0.5553972	0.4446028	0.5553972	Unhelpful-Outcome	15.59
## 60	0.3739992	0.6260008	0.6260008	0.3739992	Unhelpful-Outcome	16.42
## 61	0.4187752	0.5812248	0.5812248	0.4187752	Unhelpful-Outcome	15.85
## 62	0.6731134	0.3268866	0.3268866	0.6731134	Unhelpful-Outcome	8.62
## 63	0.4357903	0.5642097	0.4357903	0.5642097	Unhelpful-Outcome	14.85
## 64	0.3298539	0.6701461	0.3298539	0.6701461	Unhelpful-Outcome	16.05
## 65	0.6281866	0.3718134	0.3718134	0.6281866	Unhelpful-Outcome	7.73
## 66	0.3648828	0.6351172	0.3648828	0.6351172	Unhelpful-Outcome	14.36
## 67	0.8252570	0.1747430	0.1747430	0.8252570	Unhelpful-Outcome	4.76
## 68	0.5947740	0.4052260	0.4052260	0.5947740	Unhelpful-Outcome	9.77
## 69	0.5930931	0.4069069	0.4069069	0.5930931	Unhelpful-Outcome	8.13
## 70	0.3445922	0.6554078	0.6554078	0.3445922	Unhelpful-Outcome	18.24
## 71	0.3395818	0.6604182	0.3395818	0.6604182	Unhelpful-Outcome	18.32
## 72	0.3535389	0.6464611	0.3535389	0.6464611	Unhelpful-Outcome	18.45

## 73	0.1763140	0.8236860	0.1763140	0.8236860	Unhelpful-Outcome	12.38
## 74	0.5821918	0.4178082	0.4178082	0.5821918	Unhelpful-Outcome	11.59
## 75	0.4608795	0.5391205	0.4608795	0.5391205	Unhelpful-Outcome	9.44
## 76	0.3057247	0.6942753	0.3057247	0.6942753	Unhelpful-Outcome	17.10
## 77	0.4389037	0.5610963	0.5610963	0.4389037	Unhelpful-Outcome	14.74
## 78	0.6782960	0.3217040	0.3217040	0.6782960	Unhelpful-Outcome	8.76
## 79	0.4207363	0.5792637	0.4207363	0.5792637	Unhelpful-Outcome	15.42
## 80	0.4221521	0.5778479	0.4221521	0.5778479	Unhelpful-Outcome	14.66
## 81	0.3082029	0.6917971	0.3082029	0.6917971	Unhelpful-Outcome	14.59
## 82	0.4023669	0.5976331	0.4023669	0.5976331	Unhelpful-Outcome	12.12
## 83	0.3102134	0.6897866	0.6897866	0.3102134	Unhelpful-Outcome	9.05
## 84	0.7152812	0.2847188	0.2847188	0.7152812	Unhelpful-Outcome	5.72
## 85	0.6777354	0.3222646	0.3222646	0.6777354	Unhelpful-Outcome	5.92
## 86	0.5690691	0.4309309	0.5690691	0.4309309	Unhelpful-Outcome	11.48
## 87	0.3273632	0.6726368	0.6726368	0.3273632	Unhelpful-Outcome	13.52
## 88	0.2685527	0.7314473	0.2685527	0.7314473	Unhelpful-Outcome	17.84
## 89	0.5474210	0.4525790	0.5474210	0.4525790	Unhelpful-Outcome	5.44
## 90	0.7948976	0.2051024	0.7948976	0.2051024	Unhelpful-Outcome	6.11
## 91	0.6300940	0.3699060	0.6300940	0.3699060	Unhelpful-Outcome	8.26
## 92	0.5525257	0.4474743	0.4474743	0.5525257	Unhelpful-Outcome	10.01
## 93	0.2382995	0.7617005	0.2382995	0.7617005	Unhelpful-Outcome	19.53
## 94	0.5924574	0.4075426	0.4075426	0.5924574	Unhelpful-Outcome	6.70
## 95	0.6414729	0.3585271	0.3585271	0.6414729	Unhelpful-Outcome	3.70
## 96	0.6406312	0.3593688	0.3593688	0.6406312	Unhelpful-Outcome	9.11
##	Outcome	Intention				
## 1	Helpful	Irrelevant				
## 2	Helpful	Irrelevant				
## 3	Helpful	Helpful				
## 4	Helpful	Irrelevant				
## 5	Helpful	Helpful				
## 6	Helpful	Irrelevant				
## 7	Helpful	Irrelevant				
## 8	Helpful	Helpful				
## 9	Helpful	Helpful				
## 10	Helpful	Helpful				
## 11	Helpful	Irrelevant				
## 12	Helpful	Helpful				
## 13	Helpful	Helpful				
## 14	Helpful	Helpful				
## 15	Helpful	Irrelevant				
## 16	Helpful	Irrelevant				
## 17	Helpful	Helpful				
## 18	Helpful	Irrelevant				
## 19	Helpful	Helpful				
## 20	Helpful	Helpful				
## 21	Helpful	Helpful				
## 22	Helpful	Helpful				
## 23	Helpful	Irrelevant				
## 24	Helpful	Irrelevant				
## 25	Helpful	Irrelevant				
## 26	Helpful	Helpful				
## 27	Helpful	Irrelevant				
## 28	Helpful	Irrelevant				
## 29	Helpful	Helpful				

30 Helpful Helpful
31 Helpful Irrelevant
32 Helpful Irrelevant
33 Helpful Irrelevant
34 Helpful Irrelevant
35 Helpful Helpful
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77 Unhelpful Irrelevant
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79 Unhelpful Helpful
80 Unhelpful Helpful
81 Unhelpful Helpful
82 Unhelpful Helpful
83 Unhelpful Irrelevant

```
## 84 Unhelpful Irrelevant
## 85 Unhelpful Irrelevant
## 86 Unhelpful      Helpful
## 87 Unhelpful Irrelevant
## 88 Unhelpful      Helpful
## 89 Unhelpful      Helpful
## 90 Unhelpful      Helpful
## 91 Unhelpful      Helpful
## 92 Unhelpful Irrelevant
## 93 Unhelpful      Helpful
## 94 Unhelpful Irrelevant
## 95 Unhelpful Irrelevant
## 96 Unhelpful Irrelevant
```

```
woo_study2_graphing <- woo_study2 %>%
  group_by(Condition, Outcome) %>%
  summarise(looking_time = mean(LT),
            sems = std.error(LT))
```

`summarise()` has grouped output by 'Condition'. You can override using the `.groups` argument.

Leonard Data Prep

```
leonard_graphing = leonard_data %>%
  group_by(version) %>%
  summarise(correct = mean(test_question),
            sems = std.error(test_question))
```

Asaba Wu Data Prep

```
asaba_graphing = asaba_data %>%
  group_by(location, outcome) %>%
  summarise(surprise_choice = mean(chose_surprise),
            sems = std.error(chose_surprise))
```

`summarise()` has grouped output by 'location'. You can override using the `.groups` argument.

Graphing

```
#liu spelke graph
ls1 <- ggplot(data = liu_graphing, aes(x = sample, y = looking_time, fill = trialtype)) +
  geom_bar(position="dodge", stat="identity") +
  geom_errorbar(aes(ymin = (looking_time - sems), ymax = (looking_time + sems)), position = position_dodge) +
  xlab("Data Collection Method") +
  ylab("Looking Time") +
  scale_fill_grey(start = .3, end = .8, name = "Outcome") +
```

```

theme_minimal() +
ggtitle("Study 4")

#woo spelke graph - inperson
w1 <- ggplot(woo_study1_graphing, aes(x = Condition, y = value, fill = Outcome)) +
  geom_bar(position="dodge", stat="identity") +
  labs(x = "Condition", y = "Number of Infants Reaching") +
  theme_minimal() +
  ggtitle("Study 3 - In-Person") +
  scale_fill_grey(start = .3, end = .8, labels = c("Unhelpful", "Helpful")) +
  ylim(c(0,25))

#woo spelke graph - online
w2 <- ggplot(woo_study2_graphing,
             aes(x = Condition, y = looking_time, fill = Outcome)) +
  geom_bar(position="dodge", stat="identity") +
  geom_errorbar(aes(ymin = (looking_time - sems), ymax = (looking_time + sems)), position = position_dodge(.9), width = 1) +
  xlab("Condition") +
  ylab("Looking Time") +
  theme_minimal() +
  ggtitle("Study 3 - Online") +
  scale_fill_grey(start = .3, end = .8, name = "Outcome")

#leonard graph
l1 <- ggplot(data = leonard_graphing, aes(x = version, y = correct)) +
  geom_bar(position="dodge", stat="identity", fill = "grey80") +
  geom_errorbar(aes(ymin = (correct - sems), ymax = (correct + sems)), position = position_dodge(.9), width = 1) +
  xlab("Data Collection Method") +
  ylab("Prop Correct") +
  geom_hline(linetype = "dashed", yintercept = 0.5) + ylim(0,1) +
  theme_minimal() +
  ggtitle("Study 1")

#asaba wu graph
a1 <- ggplot(data = asaba_graphing, aes(x = location, y = surprise_choice, fill = outcome)) +
  geom_bar(position="dodge", stat="identity") +
  geom_errorbar(aes(ymin = (surprise_choice - sems), ymax = (surprise_choice + sems)), position = position_dodge(.9), width = 1) +
  xlab("Data Collection Method") +
  ylab("Prop Surprise Choice") +
  geom_hline(linetype = "dashed", yintercept = 0.5) + ylim(0,1) +
  theme_minimal() +
  ggtitle("Study 2") +
  scale_fill_grey(start = .3, end = .8, name = "Outcome")

#cowplot::plot_grid(w1, w2, l1, a1)
ggarrange(l1, a1, arrangeGrob(w1, w2, ncol = 2), l1,
          labels = c("1", "2", "3", "4"),
          ncol = 2, nrow = 2)

```

