Physical Pragmatics (symbols_1)

Preprocessing

```
# Preprocess and merge each partition of the participant data.
data_5 = tibble()
num_participants = 0
for (partition_path in list.files(data_path, pattern="data",
                                   full.names=TRUE)) {
  # Read in the current partition of the participant data.
  data 0 = read csv(file.path(partition path, "raw data.csv"))
  # Combine the trial and exclusion columns.
  data 1 = \text{data } 0 \%
      gather(trial_type, num, trial_num, exclusion_num) %>%
      na.omit() %>%
      mutate(trial=gsub("num", "", paste(trial_type, num, sep=""))) %>%
      select(-trial type, -num) %>%
      mutate(target=gsub("\"", "", target, fixed=TRUE))
  # Read in and merge the participant age information.
  data_2 = read_csv(file.path(partition_path, "subject_information.csv")) %>%
    select(workerid, first_object, second_object, age) %>%
    mutate(age=as.numeric(gsub("\"", "", age))) %>%
    right_join(data_1)
  # Import the setup information to know which side the low-cost door was on.
  setup_0 = read_tsv(file.path(partition_path, "trial_information.tsv")) %>%
    select(workerid, Answer.setup)
  # Remove the quotes, backslashes, and braces.
  setup_1 = setup_0 %>%
    mutate(Answer.setup=gsub("\\", "", Answer.setup, fixed=TRUE)) %>%
    mutate(Answer.setup=gsub("\"", "", Answer.setup, fixed=TRUE)) %>%
mutate(Answer.setup=gsub("{", "", Answer.setup, fixed=TRUE)) %>%
    mutate(Answer.setup=gsub("}", "", Answer.setup, fixed=TRUE))
  # Extract all relevant trial information.
  setup_2 = setup_1 %>%
    separate(Answer.setup,
             into=c("condition", "first_side", "second_side",
                   "first_object", "second_object", "doors"),
             sep=",") %>%
    mutate(condition=gsub("condition:", "", condition),
           first side=gsub("first side:", "", first side),
           second_side=gsub("second_side:", "", second_side),
```

```
first_object=gsub("first_object:", "", first_object),
         second_object=gsub("second_object:", "", second_object),
         doors=gsub("doors:", "", doors)) %>%
 mutate(first_object=gsub("fishbowl", "string", first_object),
         second_object=gsub("fishbowl", "string", second_object))
# Merge the trial information with the participant data and remake the
# participant column.
data 3 = \text{data } 2 \%
  select(workerid, first_object, second_object, age) %>%
 unique() %>%
 rownames_to_column(var="participant") %>%
 mutate(participant=as.numeric(participant)+num_participants) %>%
 right_join(left_join(data_2, setup_2)) %>%
  select(-workerid)
# Update the current number of participants.
num_participants = num_participants + length(unique(data_3$participant))
# Exclude participants that did not say the modified door is harder to walk
# through on the low-cost trial.
data_4 = data_3 %>%
 filter(trial=="exclusion_1", target==first_side) %>%
 select(participant) %>%
 left join(data 3)
# Write the current partition of the preprocessed data.
write_csv(data_4, file.path(partition_path, "data.csv"))
# Merge the current partition of participant data with the rest.
data_5 = data_5 \%
 rbind(data_4)
```

Compute Door Endorsements

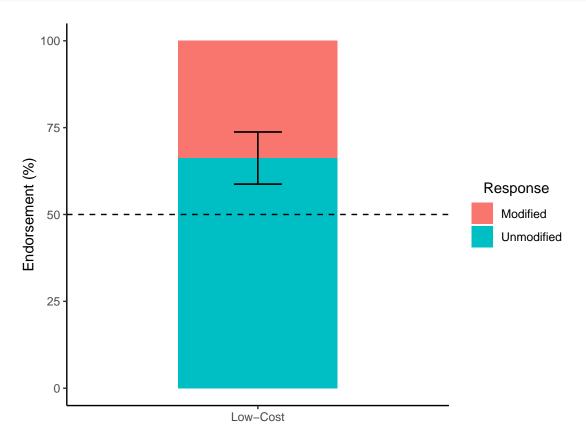
Here we compute the participant door endorsements (N=160, M=36.13 years, SD=10.9 years) for each of our trials.

decider_0 Replication

First, we'll analyze the low-cost trial, which serves as a replication of decider_0. Since the low-cost trials are identical across conditions, we analyze them jointly.

```
# Filter the data from the low-cost trial.
data_6 = data_5 %>%
  filter(trial=="trial_1") %>%
  mutate(target=as.numeric(target))
# Set up the bootstrap functions.
compute mean = function(data, indices) {
 return(mean(data[indices]))
}
compute_bootstrap = function(data) {
  simulations = boot(data=data$target,
                     statistic=compute_mean,
                     R=10000)
 return(boot.ci(simulations, type="perc")$perc)
}
# Compute the bootstrapped 95% CIs for the participant endorsement of the
# unmodified door in the low-cost trial.
set.seed(seed)
bootstrap_data = compute_bootstrap(data_6)
ci = data.frame(trial="trial 1",
                lower_ci=bootstrap_data[4]*100,
                upper_ci=bootstrap_data[5]*100)
# Compute the participant endorsement for the unmodified door in the low-cost
# trial.
data_7 = data_6 \%
  group_by(trial) %>%
  summarize(unmodified=sum(target)/n()*100) %>%
  mutate(modified=100-unmodified) %>%
 left_join(ci) %>%
  gather(door, endorsement, unmodified, modified)
# Plot the participant endorsement for the unmodified door in the low-cost
# trial, which is a replication of 'decider_0'.
plot_0 = data_7 %>%
  ggplot(aes(x=trial, y=endorsement, fill=door)) +
  geom_bar(stat="identity", width=0.5) +
  geom_errorbar(aes(ymin=lower_ci, ymax=upper_ci), width=0.15) +
  geom_hline(yintercept=50, linetype="dashed", color="black") +
  theme classic() +
  theme(aspect.ratio=1.0,
        legend.title=element_text(hjust=0.5)) +
  scale_x_discrete(name="",
                   limits=c("trial_1"),
                   labels=c("Low-Cost")) +
  ylab("Endorsement (%)") +
  scale_fill_discrete(name="Response",
                      limits=c("modified", "unmodified"),
```

```
labels=c("Modified", "Unmodified"))
plot_0
```

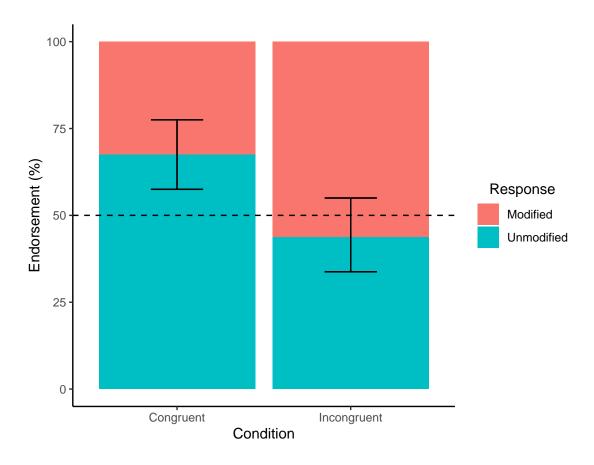


```
##
## Exact binomial test
##
## data: sum(data_6$target) and length(data_6$target)
## number of successes = 106, number of trials = 160, p-value = 4.8e-05
## alternative hypothesis: true probability of success is not equal to 0.5
## 95 percent confidence interval:
## 0.5836060 0.7352473
## sample estimates:
## probability of success
## 0.6625
```

Main Results

Now, we'll analyze our main results, comparing the participant door endorsements per condition in the symbol trial.

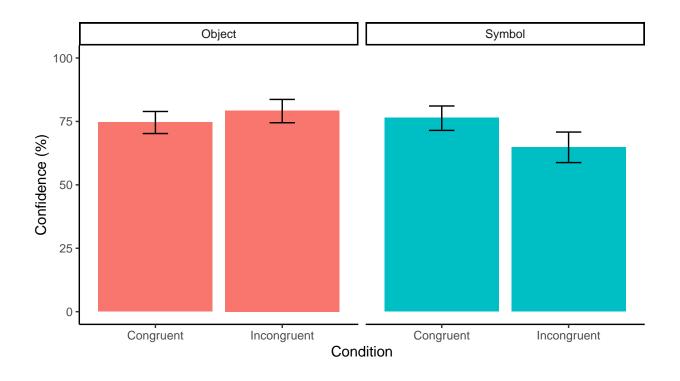
```
# Filter the data from the symbol trial.
data_8 = data_5 %>%
  filter(trial=="trial 3") %>%
  mutate(target=as.numeric(target))
# Compute the bootstrapped 95% CIs for the participant endorsement of the
# unmodified door in the symbol trial.
set.seed(seed)
ci = data.frame()
for (c in unique(data_8$condition)) {
  # Filter the relevant data for the current condition.
  data_9 = data_8 %>%
    filter(condition==c)
  # Compute the bootstrapped 95% CIs.
  bootstrap_data = compute_bootstrap(data_9)
  ci = rbind(ci, data.frame(trial="trial_3",
                            condition=c,
                            lower_ci=bootstrap_data[4]*100,
                            upper_ci=bootstrap_data[5]*100))
}
# Compute the participant endorsement for the unmodified door in the symbol
# trial.
data_10 = data_8 %>%
  group_by(trial, condition) %>%
  summarize(unmodified=sum(target)/n()*100) %>%
  mutate(modified=100-unmodified) %>%
  left_join(ci) %>%
  gather(door, endorsement, unmodified, modified)
# Plot the participant endorsement for the unmodified door in the symbol trial.
plot_1 = data_10 %>%
  ggplot(aes(x=condition, y=endorsement, fill=door)) +
  geom_histogram(stat="identity") +
  geom_errorbar(aes(ymin=lower_ci, ymax=upper_ci), width=0.3) +
  geom_hline(yintercept=50, linetype="dashed", color="black") +
  theme classic() +
  theme(aspect.ratio=1.0,
        legend.title=element_text(hjust=0.5)) +
  scale_x_discrete(name="Condition",
                   limits=c("congruent", "incongruent"),
                   labels=c("Congruent", "Incongruent")) +
  ylab("Endorsement (%)") +
  scale_fill_discrete(name="Response",
                      limits=c("modified", "unmodified"),
                      labels=c("Modified", "Unmodified"))
plot_1
```



```
## Generalized linear mixed model fit by maximum likelihood (Laplace
     Approximation) [glmerMod]
##
   Family: binomial (logit)
## Formula: target ~ condition + (1 | first_object) + (1 | second_object)
##
     Data: data_8
##
##
        AIC
                 BIC
                       logLik deviance df.resid
##
      212.1
               224.4
                       -102.0
                                 204.1
                                            156
##
## Scaled residuals:
##
                1Q Median
                                3Q
                                       Max
## -2.1686 -0.8703 0.5005 0.7870 1.9779
##
## Random effects:
                              Variance Std.Dev.
## Groups
                 Name
## first_object (Intercept) 0.0000
                                       0.0000
## second_object (Intercept) 0.4605
                                       0.6786
## Number of obs: 160, groups: first_object, 8; second_object, 8
##
```

```
## Fixed effects:
##
                       Estimate Std. Error z value Pr(>|z|)
                                  0.3489 2.300 0.02143 *
## (Intercept)
                         0.8025
## conditionincongruent -1.0862
                                    0.3494 -3.109 0.00188 **
## Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' 1
## Correlation of Fixed Effects:
##
               (Intr)
## cndtnncngrn -0.532
## optimizer (Nelder_Mead) convergence code: 0 (OK)
## boundary (singular) fit: see ?isSingular
# Compute a binomial test on the alternative hypothesis that the participant
# endorsement for the symbol door is above chance for an initial
# low-cost door.
# NOTE: Computing a two-sided binomial test for "conservativeness".
data_11 = data_8 %>%
 filter(condition=="congruent")
binom.test(x=sum(data_11$target), n=length(data_11$target), p=0.5,
          alternative="two.sided")
##
## Exact binomial test
## data: sum(data_11$target) and length(data_11$target)
## number of successes = 54, number of trials = 80, p-value = 0.002325
## alternative hypothesis: true probability of success is not equal to 0.5
## 95 percent confidence interval:
## 0.5610630 0.7755404
## sample estimates:
## probability of success
##
                    0.675
data_12 = data_8 %>%
 filter(condition=="incongruent")
binom.test(x=sum(data_12$target), n=length(data_12$target), p=0.5,
          alternative="two.sided")
##
## Exact binomial test
##
## data: sum(data_12$target) and length(data_12$target)
## number of successes = 35, number of trials = 80, p-value = 0.3143
## alternative hypothesis: true probability of success is not equal to 0.5
## 95 percent confidence interval:
## 0.3267640 0.5530024
## sample estimates:
## probability of success
##
                   0.4375
```

```
# Compute the bootstrapped 95% CIs for participant confidence in both trials
# across both conditions.
set.seed(seed)
ci = data.frame()
for (c in unique(data_5$condition)) {
  for (t in c("trial_2", "trial_4")) {
    # Filter the relevant data for the current condition and trial.
    data 13 = data 5 %>%
      filter(condition==c, trial==t) %>%
      mutate(target=as.numeric(target))
    # Compute the bootstrapped 95% CIs.
    bootstrap_data = compute_bootstrap(data_13)
    ci = rbind(ci, data.frame(condition=c,
                              trial=t,
                              lower_ci=bootstrap_data[4],
                              upper_ci=bootstrap_data[5]))
 }
}
# Compute the participant confidence in both trials across both conditions.
data_14 = data_5 %>%
  filter(trial %in% c("trial_2", "trial_4")) %>%
  mutate(target=as.numeric(target)) %>%
  group by (condition, trial) %>%
  summarize(confidence=mean(target)*100) %>%
  ungroup() %>%
  left_join(ci) %>%
  mutate(lower_ci=lower_ci*100, upper_ci=upper_ci*100)
# Plot the participant confidence in both trials across both conditions.
plot_2 = data_14 %>%
  ggplot(aes(x=condition, y=confidence, fill=trial)) +
  geom_bar(stat="identity") +
  theme_classic() +
  theme(aspect.ratio=1.0,
        legend.position="none") +
  facet_wrap(~factor(trial,
                     levels=c("trial_2", "trial_4"),
                     labels=c("Object", "Symbol"))) +
  geom_errorbar(aes(ymin=lower_ci, ymax=upper_ci), width=0.2) +
  ylim(c(0, 100)) +
  scale x discrete(name="Condition",
                   limits=c("congruent", "incongruent"),
                   labels=c("Congruent", "Incongruent")) +
  ylab("Confidence (%)")
plot_2
```



```
# Set up the bootstrap functions.
compute_difference = function(data, indices) {
  congruent_data = data[indices,] %>%
   filter(condition=="congruent", trial=="trial_4") %>%
   mutate(target=as.numeric(target))
  incongruent_data = data[indices,] %>%
   filter(condition=="incongruent", trial=="trial_4") %>%
   mutate(target=as.numeric(target))
  return(mean(congruent_data$target)-mean(incongruent_data$target))
}
compute_bootstrap = function(data) {
  simulations = boot(data=data,
                     statistic=compute_difference,
                     R=10000)
  return(boot.ci(simulations, type="perc")$perc)
}
# Compute the boostrapped 95% CI for the difference between the mean
# participant confidence judgments in the symbol trial.
set.seed(seed)
bootstrap_data = compute_bootstrap(data_5)
difference_lower_ci = bootstrap_data[4] * 100
difference_upper_ci = bootstrap_data[5] * 100
```

```
# Compute the difference between the mean participant confidence judgments in
# the symbol trial.
difference =
 filter(data_14, condition=="congruent", trial=="trial_4")$confidence -
 filter(data_14, condition=="incongruent", trial=="trial_4")$confidence
print(paste("Difference CI (lower):", round(difference_lower_ci, 2), sep=" "))
## [1] "Difference CI (lower): 3.8"
print(paste("Difference CI (upper):", round(difference_upper_ci, 2), sep=" "))
## [1] "Difference CI (upper): 19.23"
print(paste("Difference:", difference, sep=" "))
## [1] "Difference: 11.625"
# Compute a U test between participant confidence in the symbol trial of both
# conditions.
data_15 = data_5 %>%
 filter(condition=="congruent", trial=="trial_4") %>%
 mutate(target=as.numeric(target))
data 16 = \text{data } 5 \%
 filter(condition=="incongruent", trial=="trial_4") %>%
 mutate(target=as.numeric(target))
wilcox.test(data_15$target, data_16$target)
##
## Wilcoxon rank sum test with continuity correction
## data: data_15$target and data_16$target
## W = 3978, p-value = 0.007916
## alternative hypothesis: true location shift is not equal to 0
# Set up the bootstrap functions.
compute mean = function(data, indices) {
  return(mean(data[indices]))
}
compute_bootstrap = function(data) {
  simulations = boot(data=data$target,
                     statistic=compute_mean,
                     R=10000)
  return(boot.ci(simulations, type="perc")$perc)
}
# Filter the confidence ratings for the object trial in both conditions.
data_17 = data_5 %>%
 filter(trial=="trial_2") %>%
```

```
mutate(target=as.numeric(target))
# Compute the bootstrapped 95% CIs for the average participant confidence in
# the object trial across both conditions.
set.seed(seed)
bootstrap_data = compute_bootstrap(data_17)
confidence_lower_ci = bootstrap_data[4] * 100
confidence_upper_ci = bootstrap_data[5] * 100
# Print the average participant confidence and 95% CIs in the object trial
# across both conditions.
confidence = mean(data_17$target) * 100
print(paste("Average Confidence CI (lower):", round(confidence_lower_ci, 2),
           sep=" "))
## [1] "Average Confidence CI (lower): 73.71"
print(paste("Average Confidence CI (upper):", round(confidence_upper_ci, 2),
            sep=" "))
## [1] "Average Confidence CI (upper): 80.03"
print(paste("Average Confidence:", confidence, sep=" "))
## [1] "Average Confidence: 76.95625"
# Compute the agreement between participant responses across trials in each
# condition.
data_18 = data_5 %>%
 filter(trial %in% c("trial_1", "trial_3")) %>%
 mutate(target=as.numeric(target)) %>%
  spread(trial, target) %>%
 group_by(condition) %>%
  summarize(agreement=sum(trial_1==trial_3)/n(), total=n()) %>%
  ungroup() %>%
  select(-total)
data_18
## # A tibble: 2 x 2
##
   condition agreement
    <chr>
                    <dbl>
##
## 1 congruent
                    0.912
## 2 incongruent
                    0.675
```