# Visualization Literacy Analysis

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### Read in data files

```
#grab files from google drive (only have to do this once)
# source("getFromGoogleDrive.R")
#get the first 6? characters of each data file
#get unique values of these
# this is list of subject ids
raw_file_names <- list.files("AccData")</pre>
first_six <- substr(raw_file_names, 1, 6)</pre>
sub_ids <- unique(first_six)</pre>
# fast_RTs <- data.frame(ParticipantId = character(),</pre>
                         TrialName = character(),
#
                          type = character(),
#
                          time = numeric()
# )
all_data <- NULL
for (i in 1:length(sub_ids)){
  if (grepl("~$", sub_ids[i], fixed = T)){
    next
 }
  temp_file1 <- read_xlsx(paste0("AccData/", sub_ids[i], "_1.xlsx")) %>%
    slice(1:17) %>%
    select(-starts_with("Order")) %>%
    rename(correct = 8)
  temp_file2 <- read_xlsx(paste0("AccData/", sub_ids[i], "_2.xlsx")) %>%
    slice(1:17) %>%
     select(-starts_with("Order")) %>%
    rename(correct = 8)
  new_temp <- temp_file1 %>%
    bind_cols(temp_file2$correct) %>%
    rename(Correct_1 = correct, Correct_2 = "...9") %>%
    mutate(AnswerRT = TimeToBeginInput - TimeToReadQuestion)
```

```
all_data <- all_data %>%
    bind_rows(new_temp)
}
all_data <- all_data %>%
    rename(readRT = TimeToReadQuestion, totalRT = TimeToBeginInput)
#read in trialtype key (I created this from an early version of the previous paper)
trial_type_key <- read.csv("trial_type_key.csv", stringsAsFactors = F)
all_data <- all_data %>%
    mutate(TrialType = trial_type_key$TrialType[match(TrialName, trial_type_key$TrialName)]) %>%
    mutate(TrialType = paste0("Type",TrialType))
```

### Basic checks

```
#how many participants per condition
all_data %>%
  group_by(ParticipantId, Condition) %>%
  summarize(ntrials = n()) %>%
  group_by(Condition) %>%
  summarize(nsubs = n()) %>%
  kable()
```

 $\verb|##"summarise()" has grouped output by 'ParticipantId'. You can override using the `.groups` argument.$ 

Condition	nsubs
VR	50
VR Monitor	39
VR Monitor Stereo	33

```
#why is the balance so off?
```

### Remove outliers based on RT

```
#removing on trial-by-trial basis

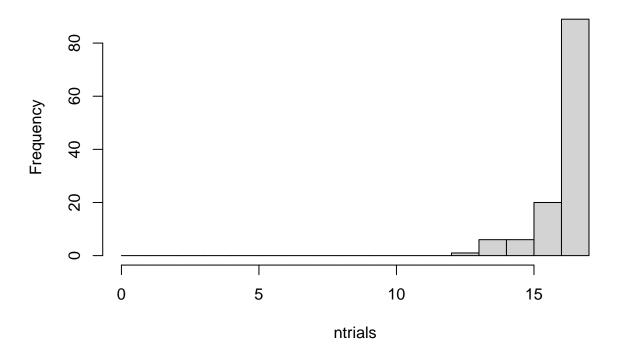
#remove answerRTs below 2000ms first
all_data_remove <- all_data %>%
    filter(AnswerRT >= 2000)
dim(all_data)[1]

## [1] 2074
dim(all_data_remove)[1]

## [1] 2067
```

```
#drops 7 trials
rt_data_summary <- all_data %>%
  group_by(TrialName) %>%
  summarize(meanAnswerRT = mean(AnswerRT, na.rm = T),
            sdAnswerRT = sd(AnswerRT, na.rm = T),
            UB = meanAnswerRT + 3*sdAnswerRT,
            LB = meanAnswerRT - 3*sdAnswerRT)
rt_data_summary
## # A tibble: 17 x 5
##
      TrialName
                    meanAnswerRT sdAnswerRT
                                                  UB
                                                          LB
##
      <chr>
                           <dbl>
                                       <dbl>
                                               <dbl>
                                                       <dbl>
   1 BarChartQ1
                          27611.
                                              71897. -16675.
##
                                      14762.
   2 BarChartQ2
##
                          16921.
                                      13338.
                                              56935. -23093.
## 3 BarChartQ3
                          15609.
                                      9948. 45452. -14235.
## 4 BarChartQ4
                          10288.
                                       8978. 37222. -16646.
## 5 LineChartQ1
                          49185.
                                      29505. 137699. -39329.
## 6 LineChartQ2
                          40127.
                                      31660. 135107. -54854.
## 7 LineChartQ3
                                      17504. 79701. -25322.
                          27190.
## 8 LineChartQ4
                          14779.
                                      16568. 64483. -34925.
## 9 LineChartQ5
                                      17250. 79628. -23874.
                          27877.
## 10 ScatterplotQ1
                          32801.
                                      24294. 105682. -40080.
## 11 ScatterplotQ2
                          29636.
                                      23980. 101576. -42304.
                                      33014. 144623. -53463.
## 12 ScatterplotQ3
                          45580.
## 13 ScatterplotQ4
                          35987.
                                      25402. 112194. -40219.
## 14 ScatterplotQ5
                          59805.
                                      42684. 187859. -68248.
## 15 SurfacePlotQ1
                          56608.
                                      36042. 164733. -51516.
## 16 SurfacePlotQ2
                                      50062. 215297. -85076.
                          65110.
## 17 SurfacePlotQ3
                          48373.
                                      37424. 160646. -63900.
all_data_no_outliers <- all_data_remove %>%
  group_by(TrialName) %>%
  filter((!(abs(AnswerRT - mean(AnswerRT)) > 3*sd(AnswerRT))))
dim(all_data_no_outliers)[1]
## [1] 2020
#drops 47 more trials
all_data_no_outliers %>%
  group_by(ParticipantId) %>%
  summarize(ntrials = n()) %>%
  with(hist(ntrials, breaks = 0:17))
```

## Histogram of ntrials

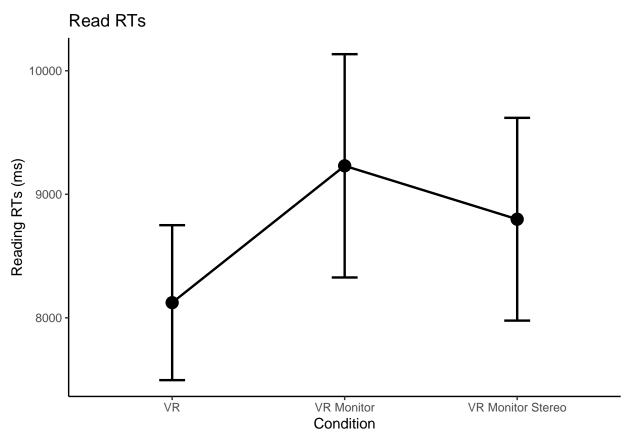


##maybe consider replacing outliers with means instead of removing them?

Compare RTs for conditions and question type (three types: identify, relate, predict)

## `summarise()` has grouped output by 'ParticipantId', 'Condition'. You can override using the `.group
# first, make .csv files in wide format to double check in statview
read\_rt\_type\_wider <- trial\_type\_means %>%
 select(ParticipantId, Condition, TrialType, mean\_readRT) %>%
 pivot\_wider(names\_from = TrialType,values\_from = mean\_readRT)
answer\_rt\_type\_wider <- trial\_type\_means %>%
 select(ParticipantId, Condition, TrialType, mean\_answerRT) %>%
 pivot\_wider(names\_from = TrialType,values\_from = mean\_answerRT)
write.csv(read\_rt\_type\_wider, file = "readtypeRTs.csv", row.names = F)
write.csv(answer\_rt\_type\_wider, file = "answertypeRTs.csv", row.names = F)

```
#### READ RTs ####
#make some plots
#just condition main effect
readplot1 <- all_data_no_outliers %>%
   group_by(ParticipantId, Condition) %>%
   summarize(overallmean = mean(readRT)) %>%
   group_by(Condition) %>%
   summarize(overall_condition_mean = mean(overallmean),
             se = std.error(overallmean),
             n = n(),
             CI = qt(0.975, df=n-1)*se)
## `summarise()` has grouped output by 'ParticipantId'. You can override using the `.groups` argument.
 ggplot(readplot1, aes(Condition,
                       overall_condition_mean,
                       group = 1,
                       ymin = overall_condition_mean - CI,
                       ymax = overall_condition_mean + CI)) +
   theme_classic() +
   geom_point(size = 4) +
   geom_errorbar(width = .15, size = 0.85) +
   geom\_line(size = 0.85) +
   labs(y = "Reading RTs (ms)", title = "Read RTs")
```



```
#make a little plot using wide format
superbPlot(read_rt_type_wider,
    BSFactors = "Condition",
WSFactors = "QuestionType(3)",
    variables = c("Type1", "Type2", "Type3"),
    statistic = "mean",
    errorbar
                = "CI",
    gamma
                = 0.95,
    adjustments = list(
                      = "difference"
        purpose
    plotStyle = "line",
    factorOrder = c("Condition", "QuestionType")
theme_classic() +
  theme(axis.text.x = element_text(angle = 45, vjust = 1, hjust=1))+
facet_wrap(vars(QuestionType))+
labs(y = "Reading RTs (ms)", title = "Read RTs")
```

# Read RTs 1 2 3 QuestionType 1 2 1 2 3 3 QuestionType 1 2 3 3 A 2 A 3 Condition

## Converting to factor: Condition

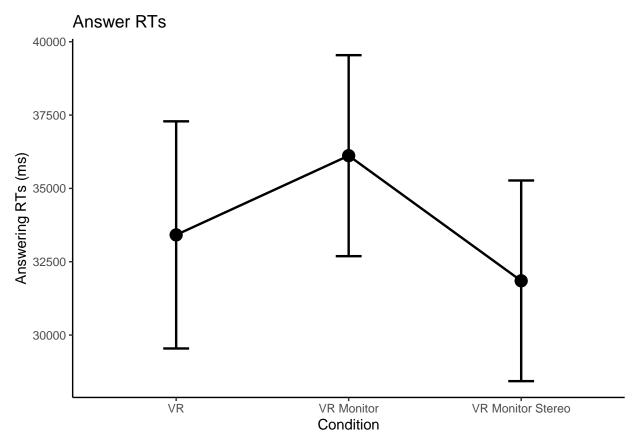
## Contrasts set to contr.sum for the following variables: Condition

kable(nice(read\_rt\_type\_anova))

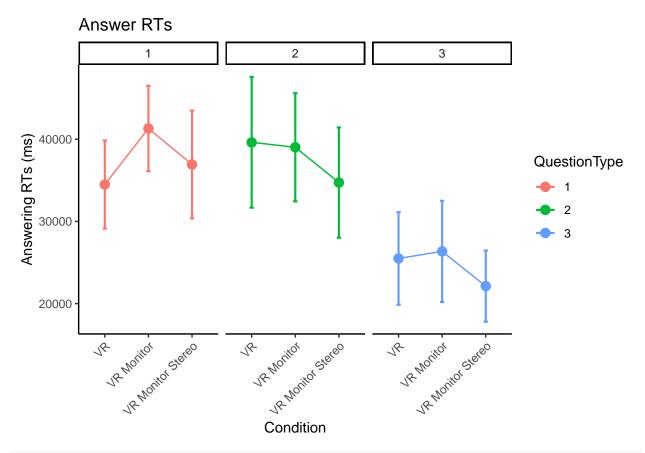
Effect	df	MSE	F	pes	p.value
Condition TrialType Condition:TrialType	2, 119	18051925.11	2.28	.037	.107
	2.00, 237.70	4660052.21	4.30 *	.035	.015
	4.00, 237.70	4660052.21	0.52	.009	.723

```
#posthoc test for trial type
pairs(emmeans(read_rt_type_anova, "TrialType"), adjust = "Tukey")
```

```
##
## Results are averaged over the levels of: Condition
## P value adjustment: tukey method for comparing a family of 3 estimates
#Question Type 2 slower than Type 1, marginally slower than Type 3 (for reading times)
#### ANSWER RTs ####
#make some plots
#just condition main effect
answerplot1 <- all_data_no_outliers %>%
   group_by(ParticipantId, Condition) %>%
   summarize(overallmean = mean(AnswerRT)) %>%
  group_by(Condition) %>%
  summarize(overall_condition_mean = mean(overallmean),
             se = std.error(overallmean),
            n = n(),
             CI = qt(0.975, df=n-1)*se)
## `summarise()` has grouped output by 'ParticipantId'. You can override using the `.groups` argument.
 ggplot(answerplot1, aes(Condition,
                       overall_condition_mean,
                       group = 1,
                       ymin = overall_condition_mean - CI,
                       ymax = overall_condition_mean + CI)) +
  theme_classic() +
  geom_point(size = 4) +
  geom_errorbar(width = .15, size = 0.85) +
  geom_line(size = 0.85) +
  labs(y = "Answering RTs (ms)", title = "Answer RTs")
```



```
#make the little plot
superbPlot(answer_rt_type_wider,
    BSFactors = "Condition",
WSFactors = "QuestionType(3)",
    variables = c("Type1", "Type2", "Type3"),
    statistic = "mean",
    errorbar
                = "CI",
    gamma
                = 0.95,
    adjustments = list(
                   = "difference"
        purpose
    plotStyle = "line",
    factorOrder = c("Condition", "QuestionType")
) +
theme_classic() +
theme(axis.text.x = element_text(angle = 45, vjust = 1, hjust=1))+
facet_wrap(vars(QuestionType))+
labs(y = "Answering RTs (ms)", title = "Answer RTs")
```



## Converting to factor: Condition

 $\mbox{\tt \#\#}$  Contrasts set to contr.sum for the following variables: Condition

kable(nice(answer\_rt\_type\_anova))

## Type2 - Type3

##

Effect	df	MSE	F	pes	p.value
Condition	2, 119	415942756.23	1.21	.020	.303
TrialType	1.93, 229.53	92112713.90	75.40 ***	.388	<.001
Condition:TrialType	3.86, 229.53	92112713.90	2.52 *	.041	.044

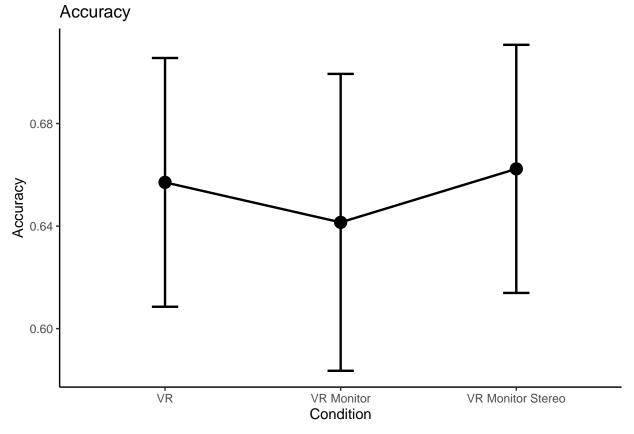
13127 1334 119

9.837 <.0001

```
## Results are averaged over the levels of: Condition
## P value adjustment: tukey method for comparing a family of 3 estimates
#Question Type 3 much faster than Type 1/Type 2 (this is answering times)
ref <- emmeans(answer_rt_type_anova,~Condition|TrialType)</pre>
pairs(ref, adjust = "Tukey")
## TrialType = Type1:
## contrast
                                  estimate SE df t.ratio p.value
## VR - VR Monitor
                                    -6816 2704 119 -2.521 0.0346
## VR - VR Monitor Stereo
                                   -2434 2839 119 -0.857 0.6682
## VR Monitor - VR Monitor Stereo 4382 2994 119 1.464 0.3121
##
## TrialType = Type2:
## contrast
                                 estimate
                                            SE df t.ratio p.value
## VR - VR Monitor
                                      595 3542 119
                                                     0.168 0.9846
## VR - VR Monitor Stereo
                                     4887 3718 119
                                                     1.314 0.3900
## VR Monitor - VR Monitor Stereo
                                     4292 3921 119
                                                     1.095 0.5192
##
## TrialType = Type3:
## contrast
                                  estimate SE df t.ratio p.value
## VR - VR Monitor
                                   -859 2690 119 -0.319 0.9453
## VR - VR Monitor Stereo
                                     3364 2824 119
                                                    1.191 0.4608
## VR Monitor - VR Monitor Stereo
                                     4223 2978 119
                                                     1.418 0.3350
## P value adjustment: tukey method for comparing a family of 3 estimates
#plot and interaction suggests that the conditions have different effects for different
#question types. posthoc tests indicate a difference between VR and VRMonitor for QType 1
```

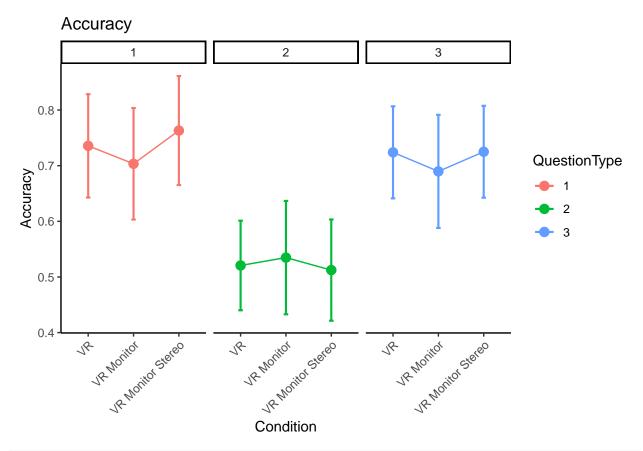
### Accuracy

```
# do interrater reliability?
# account for non-independence? idk
icc(select(ungroup(all_data_no_outliers), Correct_1, Correct_2))
  Single Score Intraclass Correlation
##
##
     Model: oneway
##
      Type : consistency
##
      Subjects = 2020
##
##
       Raters = 2
       ICC(1) = 0.934
##
##
## F-Test, H0: r0 = 0; H1: r0 > 0
## F(2019,2020) = 29.5 , p = 0
##
## 95%-Confidence Interval for ICC Population Values:
   0.929 < ICC < 0.94
all_data_no_outliers <- all_data_no_outliers %>%
rowwise() %>%
```



trial\_type\_mean\_acc <- all\_data\_no\_outliers %>%
group\_by(ParticipantId, Condition, TrialType) %>%

```
summarize(mean_acc = mean(Correct_Avg),
           n = n()
## `summarise()` has grouped output by 'ParticipantId', 'Condition'. You can override using the `.group
acc_type_wider <- trial_type_mean_acc %>%
  select(ParticipantId, Condition, TrialType, mean_acc) %>%
 pivot_wider(names_from = TrialType, values_from = mean_acc)
write.csv(acc_type_wider, file = "typeacc.csv", row.names = F)
#make the little plot
superbPlot(acc_type_wider,
   BSFactors = "Condition",
   WSFactors = "QuestionType(3)",
   variables = c("Type1", "Type2", "Type3"),
   statistic = "mean",
   errorbar = "CI",
   gamma
          = 0.95,
   adjustments = list(
       purpose = "difference"
   plotStyle = "line",
   factorOrder = c("Condition", "QuestionType")
) +
theme_classic() +
theme(axis.text.x = element_text(angle = 45, vjust = 1, hjust=1))+
facet_wrap(vars(QuestionType))+
labs(y = "Accuracy", title = "Accuracy")
```



## Converting to factor: Condition

## Contrasts set to contr.sum for the following variables: Condition

kable(nice(acc\_type\_anova))

Effect	df	MSE	F	pes	p.value
Condition TrialType Condition:TrialType	2, 119	0.08	0.22	.004	.807
	1.98, 235.08	0.02	66.89 ***	.360	<.001
	3.95, 235.08	0.02	0.74	.012	.566