Likert Scale Analysis

Michael Sun

January 14, 2024

Likert Scales

In the realm of UI/UX research, Likert scales play a pivotal role in quantitatively capturing opinions, attitudes, and responses to various questions. These scales, typically ranging from "strongly disagree" to "strongly agree," offer a simple yet powerful way for respondents to express their level of agreement with a given statement. The versatility of Likert scales makes them a staple in HCI.

For a list of Likert scale examples, see here.

BEFORE YOU BEGIN

This guide uses R to read the data from an Excel file, generate plots, summary statistics, and conduct the analysis. Please install an IDE that supports R programming, such as RStudio or PyCharm with the R plugin.

Step 1: Preparing Data

At this point, you should have a set of survey responses to one or more Likert scale questions.

The responses should be stored in an Excel file, with each row representing a respondent. Each question gets its own column, though how the design prototype is incorporated is dependent on whether you ran a between or within-subjects design experiment.

Experimental Design

- * If you ran a **between-subjects** design, you only need a column for the prototype version.
- * If you ran a within-subjects design, you should have one column for the prototype version and another column for a user's identifier (e.g., participant ID).

In either case, the remainder of your columns should correspond to each Likert scale question.

This is an example of what your Excel file should look like for a between-subjects design:

	Α	В	С	D	E	F	G	н
1	Version	Question_1	Question_2	Question_3	Question_4	Question_5	Question_6	Question_7
2	A	5	4	2	5	4	4	5
3	Α	3	4	1	4	5	3	2
4	Α	4	3	3	3	4	2	3
5	Α	5	3	2	3	4	3	3
6	Α	5	3	3	2	2	2	5
7	Α	2	3	2	3	4	4	3
8	Α	4	4	2	3	3	5	2
9	Α	3	1	3	3	4	4	2
10	Α	3	3	4	2	4	3	3
11	Α	3	3	4	4	1	3	5
12	Α	3	2	4	3	3	4	3
13	Α	5	5	2	3	3	3	4
14	Α	4	3	4	3	3	3	3
15	Α	3	5	4	2	1	1	3
16	Α	3	2	3	2	2	2	5

And for a within-subjects design:

	A	В	С	D	E	F	G	н	1
1	Participant_ID	Version	Question_1	Question_2	Question_3	Question_4	Question_5	Question_6	Question_7
2	1	Α	5	4	2	5	4	4	5
3	1	В	3	3	1	3	4	2	3
4	2	Α	3	4	1	4	5	3	2
5	2	В	3	3	3	4	3	3	2
6	3	Α	4	3	3	3	4	2	3
7	3	В	4	3	5	3	3	2	4
8	4	Α	5	3	2	3	4	3	3
9	4	В	3	2	2	4	3	3	3
10	5	Α	5	3	3	2	2	2	5
11	5	В	3	2	3	2	3	3	4
12	6	Α	2	3	2	3	4	4	3
13	6	В	2	3	2	3	4	2	2
14	7	Α	4	4	2	3	3	5	2
15	7	В	1	3	4	5	2	3	2
16	8	Α	3	1	3	3	4	4	2
17	8	В	1	3	1	2	1	1	2

Step 2: Loading Data into R

Now that you have your data in an Excel file, you can load it into R. The easiest way to do this is to use the read_excel() function from the readxl package.

If you haven't installed the package yet, be sure to uncomment the install.packages() line in the code chunk below.

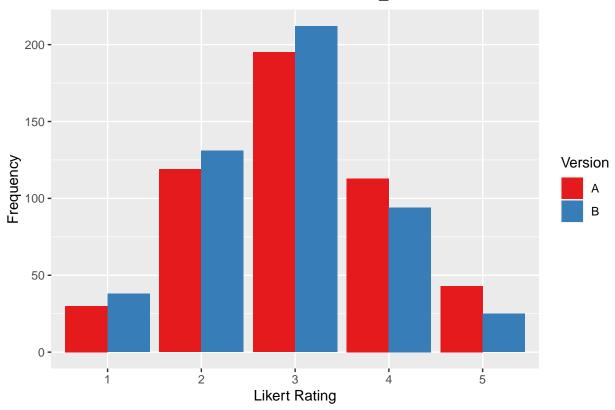
```
# install.packages("readxl")
library(readxl)
likert_data_multiple_ws <- read_excel("usability_study_likert_within_subjects_data.xlsx")</pre>
```

Step 3: Creating Plots

It may be useful to create some bar graphs to show the distribution of Likert scores by version and by question.

```
# install.packages("qqplot2")
# install.packages("dplyr")
library(ggplot2)
library(tidyr)
# Reshape the data to long format
data long <- pivot longer(likert data multiple ws,
                          cols = starts_with("Question"),
                          names to = "Question",
                          values_to = "Likert_Rating")
# Function to create a bar chart for a given question
plot_question_versions <- function(question) {</pre>
  filtered_data <- filter(data_long, Question == question)</pre>
  ggplot(filtered_data, aes(x = as.factor(Likert_Rating), fill = Version)) +
    geom_bar(position = position_dodge()) +
    scale_fill_brewer(palette = "Set1", name = "Version") +
    labs(title = paste("Bar Chart for", question),
         x = "Likert Rating",
         y = "Frequency") +
    theme(plot.title = element_text(hjust = 0.5, face = "bold"))
}
# Get unique questions
unique_questions <- unique(data_long$Question)</pre>
print(plot_question_versions(unique_questions[1]))
```





If you want to get an individual plot for each question, you can use a for loop to iterate through each question and call the plot_question_versions() function.

```
# Loop through each question and plot
for (question in unique_questions) {
  print(plot_question_versions(question))
}
```

Step 4: Creating Summary Statistics

You can also create summary statistics for each question and each version, such as the mean, median, standard deviation, minimum, and maximum.

```
# Compute summary statistics for each version and question
summary_stats_likert_multiple <- data_long %>%
group_by(Question, Version) %>%
summarize(
    Count = n(),
    Mean = mean(Likert_Rating),
    Median = median(Likert_Rating),
    Standard_Deviation = sd(Likert_Rating),
    Min = min(Likert_Rating),
    Max = max(Likert_Rating)
)
```

'summarise()' has grouped output by 'Question'. You can override using the

```
# Print the summary statistics
options(dplyr.print_max = Inf)
print(summary_stats_likert_multiple)
```

##	# 1	A tibble: 40	x 8								
##											
##		Question	Version		Mean	Median	Standard_Deviation	Min	Max		
##		<chr></chr>	<chr></chr>	<int></int>	<dbl></dbl>	<dbl></dbl>	<dbl></dbl>	<dbl></dbl>	<dbl></dbl>		
##	1	Question_1	Α	500	3.04	3	1.02	1	5		
##		Question_1	В	500	2.87	3	0.970	1	5		
##	3	Question_10	A	500	3.40	3	0.991	1	5		
##	4	Question_10	В	500	2.54	3	1.00	1	5		
##	5	Question_11	A	500	3.56	4	0.967	1	5		
##	6	Question_11	В	500	2.54	2	1.03	1	5		
##	7	Question_12	Α	500	3.49	4	0.980	1	5		
##	8	Question_12	В	500	2.43	2	1.00	1	5		
##	9	Question_13	Α	500	3.51	3	0.984	1	5		
##	10	Question_13	В	500	2.39	2	0.967	1	5		
##	11	Question_14	Α	500	3.66	4	0.935	1	5		
##	12	Question_14	В	500	2.38	2	0.952	1	5		
##	13	Question_15	Α	500	3.76	4	0.898	1	5		
##	14	Question_15	В	500	2.30	2	0.926	1	5		
##	15	Question_16	Α	500	3.73	4	0.978	1	5		
##	16	Question_16	В	500	2.28	2	0.931	1	5		
##	17	Question_17	Α	500	3.94	4	0.901	1	5		
##	18	Question_17	В	500	2.23	2	0.954	1	5		
##	19	Question_18	Α	500	3.75	4	0.971	1	5		
##	20	Question_18	В	500	2.19	2	0.943	1	5		
##	21	Question_19	Α	500	3.89	4	0.903	1	5		
##	22	Question_19	В	500	2.08	2	0.898	1	5		
##	23	Question_2	Α	500	3.15	3	0.978	1	5		
##	24	Question_2	В	500	2.89	3	1.00	1	5		
##	25	Question_20	Α	500	3.99	4	0.878	1	5		
##	26	Question_20	В	500	2.1	2	0.919	1	5		
##		Question_3	A	500	3.14	3	1.01	1	5		
##		Question_3	В	500	2.8	3	0.966	1	5		
##		Question_4	A	500	3.12	3	1.00	1	5		
##		Question_4	В	500	2.78	3	1.03	1	5		
##		Question_5	A	500	3.22	3	1.02	1	5		
##		Question_5	В	500	2.8	3	1.00	1	5		
##		Question_6	A	500	3.26	3	0.990	1	5		
		Question_6	В	500	2.70	3	0.960	1	5		
##		Question_7	A	500	3.31	3	1.04	1	5		
##		Question_7	В	500	2.70	3	0.970	1	5		
##		Question_8	A	500	3.33	3	0.967	1	5		
##		Question_8	В	500	2.57	3	0.994	1	5		
##		Question_9	A	500	3.39	3	0.975	1	5		
##	40	Question_9	В	500	2.57	3	0.977	1	5		

Step 5: Running Statistical Tests

The statistical test you run depends on the experimental design you used. For within-subjects design, you should use the Wilcoxon signed rank test. For between-subjects design, you should use the Wilcoxon rank sum test.

The Wilcoxon signed ranked test is a non-parametric test that compares two related samples. The Wilcoxon rank sum test (a.k.a. the Mean-Whitney U test) is a non-parametric test that compares two independent samples. These tests are non-parametric tests—used when the data is not normally distributed or when the sample size is small. Such is the case with Likert scale data.

Within-subjects:

```
# Initializing a dataframe to store the results
test_results <- data.frame(Question = character(),</pre>
                            Wilcoxon_Statistic = numeric(),
                            P_Value = numeric(),
                            stringsAsFactors = FALSE)
data_wide <- data_long %>%
  pivot_wider(names_from = Version, values_from = Likert_Rating)
# Looping through each question to perform the test
for (q in unique(data_long$Question)) {
  # Extracting the paired responses for each version
  responses <- filter(data_wide, Question == q)
  # Performing the Wilcoxon signed-rank test
  test <- wilcox.test(responses$`A`, responses$`B`, paired = TRUE)</pre>
  # Storing the results
  test_results <- rbind(test_results,</pre>
                         data.frame(Question = q,
                                    Wilcoxon_Statistic = test$statistic,
                                    P_Value = test$p.value))
}
# Displaying the test results
print(test_results)
```

```
##
          Question Wilcoxon_Statistic
                                            P_Value
## V
        Question_1
                              35867.0 1.757328e-02
## V1
        Question_2
                              39954.5 1.007498e-04
## V2
        Question_3
                              45495.0 7.592614e-08
## V3
        Question_4
                              44448.0 7.418933e-07
## V4
        Question_5
                              41782.0 8.047282e-11
## V5
        Question_6
                              50335.0 1.671821e-16
## V6
        Question_7
                              50244.5 2.395226e-20
## V7
        Question_8
                              58378.0 5.517323e-27
## V8
        Question 9
                              56533.0 1.509075e-30
## V9
       Question_10
                              66626.0 5.275079e-31
## V10 Question 11
                              69713.5 8.375511e-39
## V11 Question_12
                              67279.5 2.602166e-41
## V12 Question 13
                              73528.5 9.147343e-43
                              76277.5 6.002662e-53
## V13 Question_14
```

```
## V14 Question_15 81107.0 8.814582e-60
## V15 Question_16 84973.0 8.156181e-58
## V16 Question_17 92695.0 3.100225e-68
## V17 Question_18 92430.5 2.289302e-62
## V18 Question_19 94250.5 2.055136e-69
## V19 Question_20 98981.0 4.808506e-72
```

For a **between-subjects** design, you can use the Wilcoxon rank sum test. See the GitHub page for more information.