Exploratory and Statistical Analyses

June 03, 2025

Table of Contents

# Restart R / Clear Packages before running -----------------------  
#-----------------------------------------------------------------  
knitr::opts\_chunk$set(echo = TRUE, message = FALSE, warning = FALSE)  
require(tidyverse)

## Loading required package: tidyverse

## Warning: package 'stringr' was built under R version 4.4.3

## ── Attaching core tidyverse packages ──────────────────────── tidyverse 2.0.0 ──  
## ✔ dplyr 1.1.4 ✔ readr 2.1.5  
## ✔ forcats 1.0.0 ✔ stringr 1.5.1  
## ✔ ggplot2 3.5.1 ✔ tibble 3.2.1  
## ✔ lubridate 1.9.3 ✔ tidyr 1.3.1  
## ✔ purrr 1.0.2

## ── Conflicts ────────────────────────────────────────── tidyverse\_conflicts() ──  
## ✖ dplyr::filter() masks stats::filter()  
## ✖ dplyr::lag() masks stats::lag()  
## ℹ Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become errors

require(knitr)

## Loading required package: knitr

## Warning: package 'knitr' was built under R version 4.4.2

require(kableExtra)

## Loading required package: kableExtra  
##   
## Attaching package: 'kableExtra'  
##   
## The following object is masked from 'package:dplyr':  
##   
## group\_rows

require(lubridate)

### 0.0.1 Importing Data

# ---- Set Paths ----  
base <- normalizePath(file.path("..", ".."), mustWork = FALSE)  
analyses <- file.path(base, "analyses")  
inp <- file.path(analyses, "inputs")  
oup <- file.path(analyses, "outputs")  
  
# ---- Load Raw Dataset ----  
df <- read\_csv(file.path(oup, "recodeddata.csv"))  
nrow(df) # 140 responses ------

## [1] 140

names(df)

## [1] "START" "END"   
## [3] "PROG" "DURATION"   
## [5] "FINISHED" "RECORDED"   
## [7] "ID" "QSCORE"   
## [9] "DOB" "RESIDENT"   
## [11] "ZIPCODE" "RACE"   
## [13] "ETHNICITY" "GENDER"   
## [15] "INCOME" "EDUCATION"   
## [17] "DEGREE" "TWS"   
## [19] "COURSE" "COURSETIME"   
## [21] "SELFTITLE" "BIOTIME"   
## [23] "ACTIVITYfill" "ACTIVITYfill.1"   
## [25] "othACTIVITY" "AFFILIATE"   
## [27] "AFFILIATEfill" "othAFFILIATE"   
## [29] "CONTACT" "FIELD"   
## [31] "COLLECT" "HANDLE"   
## [33] "STATE" "PPE"   
## [35] "PPETIME" "COUNTIES"   
## [37] "LICENSE" "PIGS"   
## [39] "BRUCE" "CWD"   
## [41] "FLUAL" "FLU"   
## [43] "COVID" "COVIDSPILL"   
## [45] "RABIESAL" "RABIES"   
## [47] "TURKEY" "CWDAL"   
## [49] "BATS" "PPEREQ"   
## [51] "EHD" "DARWIN"   
## [53] "POPRED" "POPPLAN"   
## [55] "SURVEY" "VACCINE"   
## [57] "PREVAL" "DIVERSE"   
## [59] "CONSEQ" "CLIMATE"   
## [61] "EDREQ" "INFO"   
## [63] "HANDSON" "ACCESS"   
## [65] "SOURCE" "SOURCEfill"   
## [67] "othSOURCE" "INTEREST"   
## [69] "FREEINFO" "FREEINFOfill"   
## [71] "othFREEINFO" "TOPICS"   
## [73] "TOPICSfill" "othTOPICS"   
## [75] "QSNCS" "RACE\_BIN"   
## [77] "INCOME\_BIN" "GENDER\_BIN"   
## [79] "RESIDENT\_BIN" "AGE"   
## [81] "AGE\_BIN" "SELFTITLE\_BIN"   
## [83] "ACTIVITY" "LICENSE\_BIN"   
## [85] "BIOTIME\_BIN" "AFFILIATE\_GROUP"   
## [87] "ACTIVITY\_GROUP" "EDUCATION\_BIN"   
## [89] "DEGREE\_BIN" "TWS\_BIN"   
## [91] "COURSE\_BIN" "COURSETIME\_BIN"   
## [93] "COURSE\_GROUP" "DEMO\_EDU\_SCORE"   
## [95] "DEMO\_EDU\_NORM" "DEMO\_EDU\_AVG"   
## [97] "DEMO\_EDU\_MED" "DEMO\_EXP\_SCORE"   
## [99] "DEMO\_EXP\_NORM" "DEMO\_EXP\_AVG"   
## [101] "DEMO\_EXP\_MED" "PIGS\_BINK"   
## [103] "BRUCE\_BINK" "CWD\_BINK"   
## [105] "FLUAL\_BINK" "FLU\_BINK"   
## [107] "COVID\_BINK" "COVIDSPILL\_BINK"   
## [109] "RABIESAL\_BINK" "RABIES\_BINK"   
## [111] "TURKEY\_BINK" "KNOWLEDGE\_SCORE"   
## [113] "KNOWLEDGE\_SCORE\_NORM" "KNOWLEDGE\_AVG"   
## [115] "KNOWLEDGE\_MED" "PIGS\_BINC"   
## [117] "BRUCE\_BINC" "CWD\_BINC"   
## [119] "FLUAL\_BINC" "FLU\_BINC"   
## [121] "COVID\_BINC" "COVIDSPILL\_BINC"   
## [123] "RABIESAL\_BINC" "RABIES\_BINC"   
## [125] "TURKEY\_BINC" "CONFIDENCE\_SCORE"   
## [127] "CONFIDENCE\_SCORE\_NORM" "CONFIDENCE\_AVG"   
## [129] "CONFIDENCE\_MED" "POPRED\_A"   
## [131] "POPPLAN\_A" "SURVEY\_A"   
## [133] "VACCINE\_A" "PREVAL\_A"   
## [135] "DIVERSE\_A" "CONSEQ\_A"   
## [137] "CLIMATE\_A" "EDREQ\_A"   
## [139] "INFO\_A" "HANDSON\_A"   
## [141] "CWDAL\_A" "BATS\_A"   
## [143] "PPEREQ\_A" "EHD\_A"   
## [145] "DARWIN\_A" "ATT\_CONTROL\_SCORE"   
## [147] "ATT\_CONTROL\_NORM" "ATT\_MISINFO\_SCORE"   
## [149] "ATT\_MISINFO\_NORM" "ATT\_CONCERN\_SCORE"   
## [151] "ATT\_CONCERN\_NORM" "ATT\_EDUCATION\_SCORE"   
## [153] "ATT\_EDUCATION\_NORM" "ATT\_REVERSE\_SCORE"   
## [155] "ATT\_REVERSE\_NORM" "ATT\_DIRECT\_SCORE"   
## [157] "ATT\_DIRECT\_NORM" "CONTROL\_AVG"   
## [159] "CONTROL\_MED" "MISINFO\_AVG"   
## [161] "MISINFO\_MED" "CONCERN\_AVG"   
## [163] "CONCERN\_MED" "EDUCATION\_AVG"   
## [165] "EDUCATION\_MED" "REVERSE\_AVG"   
## [167] "REVERSE\_MED" "DIRECT\_AVG"   
## [169] "DIRECT\_MED" "TOPIC\_COUNT"   
## [171] "COLLECT\_BIN" "HANDLE\_BIN"   
## [173] "PPE\_BIN" "ACCESS\_BIN"   
## [175] "CONTACT\_BIN" "INTEREST\_BIN"   
## [177] "FIELD\_BIN\_MED" "FIELD\_BIN\_50"   
## [179] "STATE\_BIN" "PPETIME\_BIN"   
## [181] "FREEINFO\_BIN\_INPERSON" "FREEINFO\_BIN\_VIRTUAL"   
## [183] "FREEINFO\_BIN\_OTHER" "TOPIC\_BIN\_RABIES"   
## [185] "TOPIC\_BIN\_FLU" "TOPIC\_BIN\_LEPTO"   
## [187] "TOPIC\_BIN\_RR" "TOPIC\_BIN\_VECTOR"   
## [189] "TOPIC\_BIN\_CWD" "TOPIC\_BIN\_COVID"   
## [191] "TOPIC\_BIN\_ONEHEALTH" "TOPIC\_BIN\_OTHER"   
## [193] "TOPIC\_BREADTH\_BIN" "SOURCE\_BIN\_FAMILY"   
## [195] "SOURCE\_BIN\_AGENCY" "SOURCE\_BIN\_ACADEMIC"   
## [197] "SOURCE\_BIN\_SOCIAL" "SOURCE\_BIN\_NEWS"   
## [199] "SOURCE\_BIN\_CONFERENCES" "SOURCE\_BIN\_NONE"   
## [201] "SOURCE\_BIN\_OTHER" "SOURCE\_TRUST\_COUNT"   
## [203] "SOURCE\_UNTRUST\_COUNT" "SOURCE\_TRUST\_BIN"   
## [205] "PRACTICE\_EXPOSURE\_SCORE" "PRACTICE\_EXPOSURE\_NORM"   
## [207] "PRACTICE\_AVG" "PRACTICE\_MED"   
## [209] "PRACTICE\_EDUCATION\_SCORE" "PRACTICE\_EDUCATION\_NORM"

# 1 Functions

#### 1.0.0.1 Summary

# Summary for binary variables -------------  
binFUN <- function(data, var, labels = c("No", "Yes")) {  
 data %>%  
 count(!!sym(var)) %>%  
 mutate(  
 Label = case\_when(  
 !!sym(var) == 0 ~ labels[1],  
 !!sym(var) == 1 ~ labels[2],  
 TRUE ~ "Missing"),  
 Percent = round(n / sum(n, na.rm = TRUE) \* 100, 1)) %>%  
 rename(Code = !!sym(var), Count = n)  
}  
  
# Continuous summary ------------------  
contFUN <- function(data, var) {  
 dplyr::summarize(data,  
 Mean = mean(.data[[var]], na.rm = TRUE),  
 Median = median(.data[[var]], na.rm = TRUE),  
 SD = sd(.data[[var]], na.rm = TRUE),  
 Min = min(.data[[var]], na.rm = TRUE),  
 Max = max(.data[[var]], na.rm = TRUE),  
 N = sum(!is.na(.data[[var]])))  
}  
  
# Summary for categorical (ordinal/factor) variable -----------------------  
catFUN <- function(data, var) {  
 data %>%  
 count(!!sym(var)) %>%  
 mutate(Percent = round(n / sum(n, na.rm = TRUE) \* 100, 1)) %>%  
 rename(Level = !!sym(var), Count = n)  
}  
  
# Composite score summary ---------------  
compFUN <- function(data, var) {  
 dplyr::summarize(data,  
 Mean = mean(.data[[var]], na.rm = TRUE),  
 Median = median(.data[[var]], na.rm = TRUE),  
 SD = sd(.data[[var]], na.rm = TRUE),  
 Range = paste0(min(.data[[var]], na.rm = TRUE), "–", max(.data[[var]], na.rm = TRUE)),  
 N = sum(!is.na(.data[[var]])))  
}

#### 1.0.0.2 Chisq / Cramer

# ---- cramerschi Function ----  
cramerschi <- function(a, b) {  
 data.table <- table(a, b, useNA = "ifany")  
 data.chi <- chisq.test(data.table)  
 chistat <- as.numeric(data.chi$statistic)  
 chi.df <- as.integer(data.chi$parameter)  
 chi.pvalue <- data.chi$p.value  
 CramV <- as.numeric(cramerV(data.table))  
 interpret\_cramv <- function(cv) {  
 if (cv < 0.1) return("Negligible")  
 else if (cv < 0.3) return("Small")  
 else if (cv < 0.5) return("Moderate")  
 else return("Large")  
 }  
 CramV.label <- interpret\_cramv(CramV)  
 row\_totals <- rowSums(data.table)  
 col\_totals <- colSums(data.table)  
 grand\_total <- sum(data.table)  
 prop\_table <- prop.table(data.table) \* 100  
 row\_props <- prop.table(data.table, 1) \* 100  
 col\_props <- prop.table(data.table, 2) \* 100  
 expected <- round(data.chi$expected, 2)  
 result <- list(  
 chi\_statistic = chistat,  
 chi\_df = chi.df,  
 chi\_p\_value = chi.pvalue,  
 cramerV = CramV,  
 cramerV\_interpretation = CramV.label,  
 observed\_table = data.table,  
 expected\_table = expected,  
 row\_totals = row\_totals,  
 col\_totals = col\_totals,  
 grand\_total = grand\_total,  
 percent\_table = round(prop\_table, 2),  
 row\_percentages = round(row\_props, 2),  
 column\_percentages = round(col\_props, 2))  
 return(result)  
}  
  
# Output labels for easier use  
cramerschi.output.list <- c("chistat", "chi.df", "chi.pvalue", "CramV",  
 "zero\_zero", "zero\_one", "one\_zero", "one\_one",  
 "colzerotot", "colonetot")  
  
# ---- run\_chi\_batch Function ----  
run\_chi\_batch <- function(df, predictors, outcomes) {  
 out <- list()  
 for (p in predictors) {  
 for (o in outcomes) {  
 key <- paste(p, o, sep = "\_x\_")  
 sub <- df[, c(p, o)]  
 sub <- na.omit(sub)  
 if (nrow(sub) >= 5 && length(unique(sub[[1]])) > 1) {  
 res <- try(cramerschi(sub[[1]], sub[[2]]), silent = TRUE)  
 if (!inherits(res, "try-error")) {  
 out[[key]] <- res  
 }  
 }  
 }  
 }  
 return(out)  
}  
  
# Convert results to data frame summary  
extract\_summary <- function(result\_list) {  
 data.frame(  
 Variable\_Pair = names(result\_list),  
 Chi\_Square = sapply(result\_list, function(x) x$chi\_statistic),  
 df = sapply(result\_list, function(x) x$chi\_df),  
 p\_value = sapply(result\_list, function(x) x$chi\_p\_value),  
 CramerV = sapply(result\_list, function(x) x$cramerV),  
 Effect\_Size = sapply(result\_list, function(x) x$cramerV\_interpretation),  
 Significant = sapply(result\_list, function(x) x$chi\_p\_value < 0.05)  
 )  
}

# 2 Data Summary

#### 2.0.0.1 Metadata

# Progress Summary ----------------------------------------------------  
prog <- read\_csv(file.path(inp, "prog.csv"))  
nrow(prog) # 214 responses (all exported from qualtrics platform) ------

## [1] 214

progsum <- prog %>%  
 mutate(  
 prog\_bin = cut(  
 PROG, # specify the variable here!  
 breaks = seq(0, 100, by = 10),  
 include.lowest = TRUE,  
 right = FALSE,  
 labels = paste0(seq(0, 90, 10), "-", seq(10, 100, 10), "%"))) %>%  
 count(prog\_bin, name = "Respondent\_Count") %>%  
 arrange(prog\_bin)  
cat("### Survey Progress\n")

## ### Survey Progress

contFUN(df, "PROG") %>% kable(caption = "Survey Progress (0–100%)")

Survey Progress (0–100%)

| Mean | Median | SD | Min | Max | N |
| --- | --- | --- | --- | --- | --- |
| 99.67857 | 100 | 2.273614 | 77 | 100 | 140 |

# Duration Summary ---------------------------------------------  
df <- df %>%  
 mutate(DURATION\_MIN = DURATION / 60)  
cat("### Survey Duration\n")

## ### Survey Duration

contFUN(df, "DURATION") %>% kable(caption = "Duration (Seconds)")

Duration (Seconds)

| Mean | Median | SD | Min | Max | N |
| --- | --- | --- | --- | --- | --- |
| 15273.02 | 637.5 | 107229.7 | 318 | 1148659 | 140 |

contFUN(df, "DURATION\_MIN") %>% kable(caption = "Duration (Minutes)")

Duration (Minutes)

| Mean | Median | SD | Min | Max | N |
| --- | --- | --- | --- | --- | --- |
| 254.5504 | 10.625 | 1787.162 | 5.3 | 19144.32 | 140 |

df <- df %>% mutate(DURATION\_MIN = as.numeric(DURATION))  
total\_responses <- nrow(df)  
above\_60 <- sum(df$DURATION\_MIN > 60)  
duration\_table <- df %>%  
 filter(DURATION\_MIN <= 60) %>%  
 mutate(duration\_bin = cut(DURATION\_MIN, breaks = seq(0, 60, by = 5), include.lowest = TRUE, right = FALSE,  
 labels = paste0(seq(0, 55, 5), "-", seq(5, 60, 5), " Minutes"))) %>%  
 count(duration\_bin, name = "Respondent\_Count") %>%  
 mutate(Proportion = Respondent\_Count / total\_responses)  
duration\_table

## # A tibble: 0 × 3  
## # ℹ 3 variables: duration\_bin <fct>, Respondent\_Count <int>, Proportion <dbl>

# End Date - Survey Submission ------------------  
df <- df %>% mutate(END = as.Date(END, format = "%m/%d/%Y"))  
monthly\_summary <- df %>%  
 mutate(Month = format(END, "%Y-%m")) %>%  
 count(Month, name = "Respondent\_Count") %>%  
 mutate(Proportion = Respondent\_Count / sum(Respondent\_Count)) %>%  
 arrange(Month)  
kable(monthly\_summary, digits = c(NA, 0, 2), col.names = c("Month", "Number of Respondents", "Proportion of Total"),  
 caption = paste0("\*\*Survey Responses by Month\*\*\n", "Total responses:",sum(monthly\_summary$Respondent\_Count)))

**Survey Responses by Month** Total responses:140

| Month | Number of Respondents | Proportion of Total |
| --- | --- | --- |
| 2024-05 | 125 | 0.89 |
| 2024-06 | 12 | 0.09 |
| 2024-07 | 2 | 0.01 |
| 2024-08 | 1 | 0.01 |

#### 2.0.0.2 Demographic

# --- Binary Variables ---  
cat("### Gender\n")

## ### Gender

binFUN(df, "GENDER\_BIN", labels = c("Female", "Male")) %>% kable()

| Code | Count | Label | Percent |
| --- | --- | --- | --- |
| 0 | 37 | Female | 26.4 |
| 1 | 99 | Male | 70.7 |
| NA | 4 | Missing | 2.9 |

cat("### Race (Binary)\n")

## ### Race (Binary)

binFUN(df, "RACE\_BIN", labels = c("Non-White", "White")) %>% kable()

| Code | Count | Label | Percent |
| --- | --- | --- | --- |
| 0 | 10 | Non-White | 7.1 |
| 1 | 130 | White | 92.9 |

cat("### Income (Binary)\n")

## ### Income (Binary)

binFUN(df, "INCOME\_BIN", labels = c("Below $60K", "Above $60K")) %>% kable()

| Code | Count | Label | Percent |
| --- | --- | --- | --- |
| 0 | 52 | Below $60K | 37.1 |
| 1 | 88 | Above $60K | 62.9 |

cat("### Age (Above/Below Median)\n")

## ### Age (Above/Below Median)

binFUN(df, "AGE\_BIN", labels = c("Below Median", "Above Median")) %>% kable()

| Code | Count | Label | Percent |
| --- | --- | --- | --- |
| 0 | 70 | Below Median | 50 |
| 1 | 70 | Above Median | 50 |

cat("### LICENSE\_BIN\n")

## ### LICENSE\_BIN

binFUN(df, "LICENSE\_BIN") %>% kable()

| Code | Count | Label | Percent |
| --- | --- | --- | --- |
| 0 | 39 | No | 27.9 |
| 1 | 101 | Yes | 72.1 |

cat("### SELFTITLE\_BIN\n")

## ### SELFTITLE\_BIN

binFUN(df, "SELFTITLE\_BIN") %>% kable()

| Code | Count | Label | Percent |
| --- | --- | --- | --- |
| 0 | 32 | No | 22.9 |
| 1 | 108 | Yes | 77.1 |

cat("### TWS\_BIN\n")

## ### TWS\_BIN

binFUN(df, "TWS\_BIN") %>% kable()

| Code | Count | Label | Percent |
| --- | --- | --- | --- |
| 0 | 116 | No | 82.9 |
| 1 | 24 | Yes | 17.1 |

cat("### COURSE\_BIN\n")

## ### COURSE\_BIN

binFUN(df, "COURSE\_BIN") %>% kable()

| Code | Count | Label | Percent |
| --- | --- | --- | --- |
| 0 | 84 | No | 60 |
| 1 | 56 | Yes | 40 |

cat("### COURSETIME\_BIN\n")

## ### COURSETIME\_BIN

binFUN(df, "COURSETIME\_BIN", labels = c(">10 years ago", "<=10 years ago")) %>% kable()

| Code | Count | Label | Percent |
| --- | --- | --- | --- |
| 0 | 27 | >10 years ago | 19.3 |
| 1 | 29 | <=10 years ago | 20.7 |
| NA | 84 | Missing | 60.0 |

# --- Continuous Variable ---  
cat("### Age Summary (Continuous)\n")

## ### Age Summary (Continuous)

contFUN(df, "AGE") %>% kable()

| Mean | Median | SD | Min | Max | N |
| --- | --- | --- | --- | --- | --- |
| 38.8 | 36.5 | 13.05285 | 20 | 67 | 140 |

# --- Categorical Variables ---  
cat("### Race (Full Categories)\n")

## ### Race (Full Categories)

catFUN(df, "RACE") %>% kable()

| Level | Count | Percent |
| --- | --- | --- |
| Asian | 1 | 0.7 |
| Black or African American | 2 | 1.4 |
| I prefer Not to answer | 5 | 3.6 |
| Other | 2 | 1.4 |
| White | 130 | 92.9 |

cat("### Gender (Full Categories)\n")

## ### Gender (Full Categories)

catFUN(df, "GENDER") %>% kable()

| Level | Count | Percent |
| --- | --- | --- |
| Female | 37 | 26.4 |
| I prefer Not to answer | 4 | 2.9 |
| Male | 99 | 70.7 |

cat("### Income (Full Categories)\n")

## ### Income (Full Categories)

catFUN(df, "INCOME") %>% kable()

| Level | Count | Percent |
| --- | --- | --- |
| $0-20,000 | 23 | 16.4 |
| $100,001+ | 47 | 33.6 |
| $20,001-30,000 | 7 | 5.0 |
| $30,001-40,000 | 5 | 3.6 |
| $40,001-50,000 | 6 | 4.3 |
| $50,001-60,000 | 11 | 7.9 |
| $60,001-70,000 | 8 | 5.7 |
| $70,001-80,000 | 9 | 6.4 |
| $80,001-90,000 | 8 | 5.7 |
| $90,001-100,000 | 16 | 11.4 |

cat("### Education (Ordinal)\n")

## ### Education (Ordinal)

catFUN(df, "EDUCATION") %>% kable()

| Level | Count | Percent |
| --- | --- | --- |
| College Graduate/BA or BS (4-year degree) | 60 | 42.9 |
| Graduate or Professional School | 53 | 37.9 |
| High school graduate/GED | 12 | 8.6 |
| Some College/AA or AS (2-year degree) | 13 | 9.3 |
| Technical/Vocational School | 1 | 0.7 |
| NA | 1 | 0.7 |

cat("### BIOTIME (Years in Field)\n")

## ### BIOTIME (Years in Field)

catFUN(df, "BIOTIME") %>% kable()

| Level | Count | Percent |
| --- | --- | --- |
| 1-5 years | 27 | 19.3 |
| 10-20 years | 23 | 16.4 |
| 5-10 years | 28 | 20.0 |
| <1 year | 36 | 25.7 |
| >20 years | 26 | 18.6 |

cat("### COURSETIME\n")

## ### COURSETIME

catFUN(df, "COURSETIME") %>% kable()

| Level | Count | Percent |
| --- | --- | --- |
| 5-10 years | 12 | 8.6 |
| <5 years | 17 | 12.1 |
| >10 years | 27 | 19.3 |
| NA | 84 | 60.0 |

# --- Composite Scores ---  
cat("### DEMO\_EDU\_SCORE Summary\n")

## ### DEMO\_EDU\_SCORE Summary

compFUN(df, "DEMO\_EDU\_SCORE") %>% kable()

| Mean | Median | SD | Range | N |
| --- | --- | --- | --- | --- |
| 1.592857 | 2 | 0.7947347 | 0–2 | 140 |

cat("### DEMO\_EDU\_NORM Summary\n")

## ### DEMO\_EDU\_NORM Summary

compFUN(df, "DEMO\_EDU\_NORM") %>% kable()

| Mean | Median | SD | Range | N |
| --- | --- | --- | --- | --- |
| 0.7964286 | 1 | 0.3973674 | 0–1 | 140 |

cat("### DEMO\_EXP\_SCORE Summary\n")

## ### DEMO\_EXP\_SCORE Summary

compFUN(df, "DEMO\_EXP\_SCORE") %>% kable()

| Mean | Median | SD | Range | N |
| --- | --- | --- | --- | --- |
| 1.292857 | 1 | 0.9329803 | 0–3 | 140 |

cat("### DEMO\_EXP\_NORM Summary\n")

## ### DEMO\_EXP\_NORM Summary

compFUN(df, "DEMO\_EXP\_NORM") %>% kable()

| Mean | Median | SD | Range | N |
| --- | --- | --- | --- | --- |
| 0.3232143 | 0.25 | 0.2332451 | 0–0.75 | 140 |

# --- Binary Splits from Composite Scores ---  
cat("### DEMO\_EDU\_AVG (Above/Below Avg)\n")

## ### DEMO\_EDU\_AVG (Above/Below Avg)

binFUN(df, "DEMO\_EDU\_AVG", labels = c("Below Avg", "Above Avg")) %>% kable()

| Code | Count | Label | Percent |
| --- | --- | --- | --- |
| 0 | 30 | Below Avg | 21.4 |
| 1 | 110 | Above Avg | 78.6 |

cat("### DEMO\_EDU\_MED (Above/Below Median)\n")

## ### DEMO\_EDU\_MED (Above/Below Median)

binFUN(df, "DEMO\_EDU\_MED", labels = c("Below Median", "Above Median")) %>% kable()

| Code | Count | Label | Percent |
| --- | --- | --- | --- |
| 0 | 140 | Below Median | 100 |

cat("### DEMO\_EXP\_AVG (Above/Below Avg)\n")

## ### DEMO\_EXP\_AVG (Above/Below Avg)

binFUN(df, "DEMO\_EXP\_AVG", labels = c("Below Avg", "Above Avg")) %>% kable()

| Code | Count | Label | Percent |
| --- | --- | --- | --- |
| 0 | 89 | Below Avg | 63.6 |
| 1 | 51 | Above Avg | 36.4 |

cat("### DEMO\_EXP\_MED (Above/Below Median)\n")

## ### DEMO\_EXP\_MED (Above/Below Median)

binFUN(df, "DEMO\_EXP\_MED", labels = c("Below Median", "Above Median")) %>% kable()

| Code | Count | Label | Percent |
| --- | --- | --- | --- |
| 0 | 89 | Below Median | 63.6 |
| 1 | 51 | Above Median | 36.4 |

#### 2.0.0.3 Knowledge

cat("### Knowledge Item Accuracy (BINK variables)\n")

## ### Knowledge Item Accuracy (BINK variables)

binFUN(df, "PIGS\_BINK") %>% kable(caption = "PIGS\_BINK")

PIGS\_BINK

| Code | Count | Label | Percent |
| --- | --- | --- | --- |
| 0 | 10 | No | 7.1 |
| 1 | 130 | Yes | 92.9 |

binFUN(df, "BRUCE\_BINK") %>% kable(caption = "BRUCE\_BINK")

BRUCE\_BINK

| Code | Count | Label | Percent |
| --- | --- | --- | --- |
| 0 | 52 | No | 37.1 |
| 1 | 88 | Yes | 62.9 |

binFUN(df, "CWD\_BINK") %>% kable(caption = "CWD\_BINK")

CWD\_BINK

| Code | Count | Label | Percent |
| --- | --- | --- | --- |
| 0 | 25 | No | 17.9 |
| 1 | 115 | Yes | 82.1 |

binFUN(df, "FLUAL\_BINK") %>% kable(caption = "FLUAL\_BINK")

FLUAL\_BINK

| Code | Count | Label | Percent |
| --- | --- | --- | --- |
| 0 | 27 | No | 19.3 |
| 1 | 113 | Yes | 80.7 |

binFUN(df, "FLU\_BINK") %>% kable(caption = "FLU\_BINK")

FLU\_BINK

| Code | Count | Label | Percent |
| --- | --- | --- | --- |
| 0 | 14 | No | 10 |
| 1 | 126 | Yes | 90 |

binFUN(df, "COVID\_BINK") %>% kable(caption = "COVID\_BINK")

COVID\_BINK

| Code | Count | Label | Percent |
| --- | --- | --- | --- |
| 0 | 55 | No | 39.3 |
| 1 | 85 | Yes | 60.7 |

binFUN(df, "COVIDSPILL\_BINK") %>% kable(caption = "COVIDSPILL\_BINK")

COVIDSPILL\_BINK

| Code | Count | Label | Percent |
| --- | --- | --- | --- |
| 0 | 78 | No | 55.7 |
| 1 | 62 | Yes | 44.3 |

binFUN(df, "RABIESAL\_BINK") %>% kable(caption = "RABIESAL\_BINK")

RABIESAL\_BINK

| Code | Count | Label | Percent |
| --- | --- | --- | --- |
| 0 | 32 | No | 22.9 |
| 1 | 108 | Yes | 77.1 |

binFUN(df, "RABIES\_BINK") %>% kable(caption = "RABIES\_BINK")

RABIES\_BINK

| Code | Count | Label | Percent |
| --- | --- | --- | --- |
| 0 | 14 | No | 10 |
| 1 | 126 | Yes | 90 |

binFUN(df, "TURKEY\_BINK") %>% kable(caption = "TURKEY\_BINK")

TURKEY\_BINK

| Code | Count | Label | Percent |
| --- | --- | --- | --- |
| 0 | 75 | No | 53.6 |
| 1 | 65 | Yes | 46.4 |

## --- Composite Knowledge Scores ---  
cat("### Knowledge Composite Scores\n")

## ### Knowledge Composite Scores

compFUN(df, "KNOWLEDGE\_SCORE") %>% kable(caption = "Raw Score (0–10)")

Raw Score (0–10)

| Mean | Median | SD | Range | N |
| --- | --- | --- | --- | --- |
| 7.271429 | 7.5 | 2.080547 | 1–10 | 140 |

compFUN(df, "KNOWLEDGE\_SCORE\_NORM") %>% kable(caption = "Normalized Score (0–1)")

Normalized Score (0–1)

| Mean | Median | SD | Range | N |
| --- | --- | --- | --- | --- |
| 0.7271429 | 0.75 | 0.2080547 | 0.1–1 | 140 |

## --- Binarized Knowledge Outcomes ---  
binFUN(df, "KNOWLEDGE\_AVG", labels = c("Below Avg", "Above Avg")) %>% kable(caption = "Above/Below Average")

Above/Below Average

| Code | Count | Label | Percent |
| --- | --- | --- | --- |
| 0 | 70 | Below Avg | 50 |
| 1 | 70 | Above Avg | 50 |

binFUN(df, "KNOWLEDGE\_MED", labels = c("Below Median", "Above Median")) %>% kable(caption = "Above/Below Median")

Above/Below Median

| Code | Count | Label | Percent |
| --- | --- | --- | --- |
| 0 | 70 | Below Median | 50 |
| 1 | 70 | Above Median | 50 |

## --- Confidence (BINC: IDK = 1) ---  
cat("### Confidence (I Don't Know Responses)\n")

## ### Confidence (I Don't Know Responses)

binFUN(df, "PIGS\_BINC") %>% kable(caption = "PIGS\_BINC")

PIGS\_BINC

| Code | Count | Label | Percent |
| --- | --- | --- | --- |
| 0 | 132 | No | 94.3 |
| 1 | 8 | Yes | 5.7 |

binFUN(df, "BRUCE\_BINC") %>% kable(caption = "BRUCE\_BINC")

BRUCE\_BINC

| Code | Count | Label | Percent |
| --- | --- | --- | --- |
| 0 | 104 | No | 74.3 |
| 1 | 36 | Yes | 25.7 |

binFUN(df, "CWD\_BINC") %>% kable(caption = "CWD\_BINC")

CWD\_BINC

| Code | Count | Label | Percent |
| --- | --- | --- | --- |
| 0 | 134 | No | 95.7 |
| 1 | 6 | Yes | 4.3 |

binFUN(df, "FLUAL\_BINC") %>% kable(caption = "FLUAL\_BINC")

FLUAL\_BINC

| Code | Count | Label | Percent |
| --- | --- | --- | --- |
| 0 | 120 | No | 85.7 |
| 1 | 20 | Yes | 14.3 |

binFUN(df, "FLU\_BINC") %>% kable(caption = "FLU\_BINC")

FLU\_BINC

| Code | Count | Label | Percent |
| --- | --- | --- | --- |
| 0 | 128 | No | 91.4 |
| 1 | 12 | Yes | 8.6 |

binFUN(df, "COVID\_BINC") %>% kable(caption = "COVID\_BINC")

COVID\_BINC

| Code | Count | Label | Percent |
| --- | --- | --- | --- |
| 0 | 94 | No | 67.1 |
| 1 | 46 | Yes | 32.9 |

binFUN(df, "COVIDSPILL\_BINC") %>% kable(caption = "COVIDSPILL\_BINC")

COVIDSPILL\_BINC

| Code | Count | Label | Percent |
| --- | --- | --- | --- |
| 0 | 82 | No | 58.6 |
| 1 | 58 | Yes | 41.4 |

binFUN(df, "RABIESAL\_BINC") %>% kable(caption = "RABIESAL\_BINC")

RABIESAL\_BINC

| Code | Count | Label | Percent |
| --- | --- | --- | --- |
| 0 | 115 | No | 82.1 |
| 1 | 25 | Yes | 17.9 |

binFUN(df, "RABIES\_BINC") %>% kable(caption = "RABIES\_BINC")

RABIES\_BINC

| Code | Count | Label | Percent |
| --- | --- | --- | --- |
| 0 | 135 | No | 96.4 |
| 1 | 5 | Yes | 3.6 |

binFUN(df, "TURKEY\_BINC") %>% kable(caption = "TURKEY\_BINC")

TURKEY\_BINC

| Code | Count | Label | Percent |
| --- | --- | --- | --- |
| 0 | 104 | No | 74.3 |
| 1 | 36 | Yes | 25.7 |

## --- Confidence Composite Scores ---  
compFUN(df, "CONFIDENCE\_SCORE") %>% kable(caption = "Raw Confidence Score (IDK Count)")

Raw Confidence Score (IDK Count)

| Mean | Median | SD | Range | N |
| --- | --- | --- | --- | --- |
| 1.8 | 1 | 1.792069 | 0–8 | 140 |

compFUN(df, "CONFIDENCE\_SCORE\_NORM") %>% kable(caption = "Normalized Confidence Score (0–1)")

Normalized Confidence Score (0–1)

| Mean | Median | SD | Range | N |
| --- | --- | --- | --- | --- |
| 0.18 | 0.1 | 0.1792069 | 0–0.8 | 140 |

## --- Binarized Confidence Outcomes ---  
binFUN(df, "CONFIDENCE\_AVG", labels = c("Lower", "Higher")) %>% kable(caption = "Confidence vs Average")

Confidence vs Average

| Code | Count | Label | Percent |
| --- | --- | --- | --- |
| 0 | 76 | Lower | 54.3 |
| 1 | 64 | Higher | 45.7 |

binFUN(df, "CONFIDENCE\_MED", labels = c("Below Median", "Above Median")) %>% kable(caption = "Confidence vs Median")

Confidence vs Median

| Code | Count | Label | Percent |
| --- | --- | --- | --- |
| 0 | 76 | Below Median | 54.3 |
| 1 | 64 | Above Median | 45.7 |

#### 2.0.0.4 Attitudes

# --- Composite Scores: Raw ---  
cat("### Attitude Composite Scores (Raw Means)\n")

## ### Attitude Composite Scores (Raw Means)

compFUN(df, "ATT\_CONTROL\_SCORE") %>% kable(caption = "Control Attitudes")

Control Attitudes

| Mean | Median | SD | Range | N |
| --- | --- | --- | --- | --- |
| 3.554762 | 3.5 | 0.3842643 | 2.66666666666667–4.83333333333333 | 140 |

compFUN(df, "ATT\_MISINFO\_SCORE") %>% kable(caption = "Misinformation Attitudes")

Misinformation Attitudes

| Mean | Median | SD | Range | N |
| --- | --- | --- | --- | --- |
| 3.878571 | 4 | 0.6799759 | 2–5 | 140 |

compFUN(df, "ATT\_CONCERN\_SCORE") %>% kable(caption = "Concern Attitudes")

Concern Attitudes

| Mean | Median | SD | Range | N |
| --- | --- | --- | --- | --- |
| 3.330935 | 3.333333 | 0.7284161 | 1–5 | 139 |

compFUN(df, "ATT\_EDUCATION\_SCORE") %>% kable(caption = "Education Attitudes")

Education Attitudes

| Mean | Median | SD | Range | N |
| --- | --- | --- | --- | --- |
| 3.093525 | 3 | 0.6086187 | 1.66666666666667–4.66666666666667 | 139 |

compFUN(df, "ATT\_REVERSE\_SCORE") %>% kable(caption = "Reverse-Coded Attitudes")

Reverse-Coded Attitudes

| Mean | Median | SD | Range | N |
| --- | --- | --- | --- | --- |
| 3.315714 | 3.285714 | 0.4720629 | 1.71428571428571–4.57142857142857 | 140 |

compFUN(df, "ATT\_DIRECT\_SCORE") %>% kable(caption = "Direct-Coded Attitudes")

Direct-Coded Attitudes

| Mean | Median | SD | Range | N |
| --- | --- | --- | --- | --- |
| 3.633036 | 3.625 | 0.4587799 | 2.125–4.875 | 140 |

# --- Composite Scores: Normalized ---  
cat("### Attitude Composite Scores (Normalized 0–1)\n")

## ### Attitude Composite Scores (Normalized 0–1)

compFUN(df, "ATT\_CONTROL\_NORM") %>% kable(caption = "Control Attitudes (Norm)")

Control Attitudes (Norm)

| Mean | Median | SD | Range | N |
| --- | --- | --- | --- | --- |
| 0.7109524 | 0.7 | 0.0768529 | 0.533333333333333–0.966666666666667 | 140 |

compFUN(df, "ATT\_MISINFO\_NORM") %>% kable(caption = "Misinformation Attitudes (Norm)")

Misinformation Attitudes (Norm)

| Mean | Median | SD | Range | N |
| --- | --- | --- | --- | --- |
| 0.7757143 | 0.8 | 0.1359952 | 0.4–1 | 140 |

compFUN(df, "ATT\_CONCERN\_NORM") %>% kable(caption = "Concern Attitudes (Norm)")

Concern Attitudes (Norm)

| Mean | Median | SD | Range | N |
| --- | --- | --- | --- | --- |
| 0.6661871 | 0.6666667 | 0.1456832 | 0.2–1 | 139 |

compFUN(df, "ATT\_EDUCATION\_NORM") %>% kable(caption = "Education Attitudes (Norm)")

Education Attitudes (Norm)

| Mean | Median | SD | Range | N |
| --- | --- | --- | --- | --- |
| 0.618705 | 0.6 | 0.1217237 | 0.333333333333333–0.933333333333333 | 139 |

compFUN(df, "ATT\_REVERSE\_NORM") %>% kable(caption = "Reverse Attitudes (Norm)")

Reverse Attitudes (Norm)

| Mean | Median | SD | Range | N |
| --- | --- | --- | --- | --- |
| 0.6631429 | 0.6571429 | 0.0944126 | 0.342857142857143–0.914285714285714 | 140 |

compFUN(df, "ATT\_DIRECT\_NORM") %>% kable(caption = "Direct Attitudes (Norm)")

Direct Attitudes (Norm)

| Mean | Median | SD | Range | N |
| --- | --- | --- | --- | --- |
| 0.7266071 | 0.725 | 0.091756 | 0.425–0.975 | 140 |

# --- Binary Breakdown: Above/Below AVG ---  
cat("### Attitude Scores: Above vs Below Average\n")

## ### Attitude Scores: Above vs Below Average

binFUN(df, "CONTROL\_AVG", labels = c("Below Avg", "Above Avg")) %>% kable(caption = "Control Attitudes")

Control Attitudes

| Code | Count | Label | Percent |
| --- | --- | --- | --- |
| 0 | 75 | Below Avg | 53.6 |
| 1 | 65 | Above Avg | 46.4 |

binFUN(df, "MISINFO\_AVG", labels = c("Below Avg", "Above Avg")) %>% kable(caption = "Misinformation Attitudes")

Misinformation Attitudes

| Code | Count | Label | Percent |
| --- | --- | --- | --- |
| 0 | 61 | Below Avg | 43.6 |
| 1 | 79 | Above Avg | 56.4 |

binFUN(df, "CONCERN\_AVG", labels = c("Below Avg", "Above Avg")) %>% kable(caption = "Concern Attitudes")

Concern Attitudes

| Code | Count | Label | Percent |
| --- | --- | --- | --- |
| 0 | 55 | Below Avg | 39.3 |
| 1 | 84 | Above Avg | 60.0 |
| NA | 1 | Missing | 0.7 |

binFUN(df, "EDUCATION\_AVG", labels = c("Below Avg", "Above Avg")) %>% kable(caption = "Education Attitudes")

Education Attitudes

| Code | Count | Label | Percent |
| --- | --- | --- | --- |
| 0 | 76 | Below Avg | 54.3 |
| 1 | 63 | Above Avg | 45.0 |
| NA | 1 | Missing | 0.7 |

binFUN(df, "REVERSE\_AVG", labels = c("Below Avg", "Above Avg")) %>% kable(caption = "Reverse-Coded")

Reverse-Coded

| Code | Count | Label | Percent |
| --- | --- | --- | --- |
| 0 | 75 | Below Avg | 53.6 |
| 1 | 65 | Above Avg | 46.4 |

binFUN(df, "DIRECT\_AVG", labels = c("Below Avg", "Above Avg")) %>% kable(caption = "Direct-Coded")

Direct-Coded

| Code | Count | Label | Percent |
| --- | --- | --- | --- |
| 0 | 75 | Below Avg | 53.6 |
| 1 | 65 | Above Avg | 46.4 |

# --- Binary Breakdown: Above/Below Median ---  
cat("### Attitude Scores: Above vs Below Median\n")

## ### Attitude Scores: Above vs Below Median

binFUN(df, "CONTROL\_MED", labels = c("Below Median", "Above Median")) %>% kable(caption = "Control Attitudes")

Control Attitudes

| Code | Count | Label | Percent |
| --- | --- | --- | --- |
| 0 | 75 | Below Median | 53.6 |
| 1 | 65 | Above Median | 46.4 |

binFUN(df, "MISINFO\_MED", labels = c("Below Median", "Above Median")) %>% kable(caption = "Misinformation Attitudes")

Misinformation Attitudes

| Code | Count | Label | Percent |
| --- | --- | --- | --- |
| 0 | 92 | Below Median | 65.7 |
| 1 | 48 | Above Median | 34.3 |

binFUN(df, "CONCERN\_MED", labels = c("Below Median", "Above Median")) %>% kable(caption = "Concern Attitudes")

Concern Attitudes

| Code | Count | Label | Percent |
| --- | --- | --- | --- |
| 0 | 75 | Below Median | 53.6 |
| 1 | 64 | Above Median | 45.7 |
| NA | 1 | Missing | 0.7 |

binFUN(df, "EDUCATION\_MED", labels = c("Below Median", "Above Median")) %>% kable(caption = "Education Attitudes")

Education Attitudes

| Code | Count | Label | Percent |
| --- | --- | --- | --- |
| 0 | 76 | Below Median | 54.3 |
| 1 | 63 | Above Median | 45.0 |
| NA | 1 | Missing | 0.7 |

binFUN(df, "REVERSE\_MED", labels = c("Below Median", "Above Median")) %>% kable(caption = "Reverse-Coded")

Reverse-Coded

| Code | Count | Label | Percent |
| --- | --- | --- | --- |
| 0 | 75 | Below Median | 53.6 |
| 1 | 65 | Above Median | 46.4 |

binFUN(df, "DIRECT\_MED", labels = c("Below Median", "Above Median")) %>% kable(caption = "Direct-Coded")

Direct-Coded

| Code | Count | Label | Percent |
| --- | --- | --- | --- |
| 0 | 75 | Below Median | 53.6 |
| 1 | 65 | Above Median | 46.4 |

#### 2.0.0.5 Practices

# --- Binary Behavior Items (Yes = 1) ---  
cat("### Field Practices (Binary)\n")

## ### Field Practices (Binary)

binFUN(df, "COLLECT\_BIN", labels = c("No", "Yes")) %>% kable(caption = "Collected Wildlife")

Collected Wildlife

| Code | Count | Label | Percent |
| --- | --- | --- | --- |
| 0 | 77 | No | 55 |
| 1 | 63 | Yes | 45 |

binFUN(df, "HANDLE\_BIN", labels = c("No", "Yes")) %>% kable(caption = "Handled Wildlife")

Handled Wildlife

| Code | Count | Label | Percent |
| --- | --- | --- | --- |
| 0 | 88 | No | 62.9 |
| 1 | 52 | Yes | 37.1 |

binFUN(df, "PPE\_BIN", labels = c("No", "Yes")) %>% kable(caption = "Used PPE")

Used PPE

| Code | Count | Label | Percent |
| --- | --- | --- | --- |
| 0 | 22 | No | 15.7 |
| 1 | 83 | Yes | 59.3 |
| NA | 35 | Missing | 25.0 |

binFUN(df, "ACCESS\_BIN", labels = c("Yes", "No")) %>% kable(caption = "Field Access Barriers")

Field Access Barriers

| Code | Count | Label | Percent |
| --- | --- | --- | --- |
| 0 | 98 | Yes | 70.0 |
| 1 | 39 | No | 27.9 |
| NA | 3 | Missing | 2.1 |

binFUN(df, "CONTACT\_BIN", labels = c("Low", "High")) %>% kable(caption = "Frequent Contact")

Frequent Contact

| Code | Count | Label | Percent |
| --- | --- | --- | --- |
| 0 | 71 | Low | 50.7 |
| 1 | 69 | High | 49.3 |

binFUN(df, "FIELD\_BIN\_50", labels = c("Less", "More")) %>% kable(caption = "≥50 Days Field Time")

≥50 Days Field Time

| Code | Count | Label | Percent |
| --- | --- | --- | --- |
| 0 | 64 | Less | 45.7 |
| 1 | 76 | More | 54.3 |

binFUN(df, "INTEREST\_BIN", labels = c("No/Unsure", "Yes")) %>% kable(caption = "Interested in Education")

Interested in Education

| Code | Count | Label | Percent |
| --- | --- | --- | --- |
| 0 | 12 | No/Unsure | 8.6 |
| 1 | 125 | Yes | 89.3 |
| NA | 3 | Missing | 2.1 |

binFUN(df, "PPETIME\_BIN", labels = c("Low Use", "High Use")) %>% kable(caption = "PPE Use Rate")

PPE Use Rate

| Code | Count | Label | Percent |
| --- | --- | --- | --- |
| 1 | 55 | High Use | 39.3 |
| NA | 85 | Missing | 60.7 |

# --- Information Topics / Channels ---  
cat("### Wildlife Health Course (Binary Indicators)\n")

## ### Wildlife Health Course (Binary Indicators)

binFUN(df, "FREEINFO\_BIN\_INPERSON") %>% kable(caption = "Info Format: In-Person")

Info Format: In-Person

| Code | Count | Label | Percent |
| --- | --- | --- | --- |
| 0 | 53 | No | 37.9 |
| 1 | 87 | Yes | 62.1 |

binFUN(df, "FREEINFO\_BIN\_VIRTUAL") %>% kable(caption = "Info Format: Virtual")

Info Format: Virtual

| Code | Count | Label | Percent |
| --- | --- | --- | --- |
| 0 | 46 | No | 32.9 |
| 1 | 94 | Yes | 67.1 |

binFUN(df, "FREEINFO\_BIN\_OTHER") %>% kable(caption = "Info Format: Other")

Info Format: Other

| Code | Count | Label | Percent |
| --- | --- | --- | --- |
| 0 | 139 | No | 99.3 |
| 1 | 1 | Yes | 0.7 |

binFUN(df, "TOPIC\_BREADTH\_BIN", labels = c("Narrow", "Broad")) %>% kable(caption = "Topic Breadth")

Topic Breadth

| Code | Count | Label | Percent |
| --- | --- | --- | --- |
| 1 | 140 | Broad | 100 |

# --- Composite: Practice Exposure Score ---  
cat("### Composite Practice - Exposure Score\n")

## ### Composite Practice - Exposure Score

compFUN(df, "PRACTICE\_EXPOSURE\_SCORE") %>% kable(caption = "Exposure Score (0–4)")

Exposure Score (0–4)

| Mean | Median | SD | Range | N |
| --- | --- | --- | --- | --- |
| 1.857143 | 2 | 1.391503 | 0–4 | 140 |

compFUN(df, "PRACTICE\_EXPOSURE\_NORM") %>% kable(caption = "Exposure Score (Normalized 0–1)")

Exposure Score (Normalized 0–1)

| Mean | Median | SD | Range | N |
| --- | --- | --- | --- | --- |
| 0.4642857 | 0.5 | 0.3478757 | 0–1 | 140 |

binFUN(df, "PRACTICE\_AVG", labels = c("Below Avg", "Above Avg")) %>% kable(caption = "Exposure vs Average")

Exposure vs Average

| Code | Count | Label | Percent |
| --- | --- | --- | --- |
| 0 | 95 | Below Avg | 67.9 |
| 1 | 45 | Above Avg | 32.1 |

binFUN(df, "PRACTICE\_MED", labels = c("Below Median", "Above Median")) %>% kable(caption = "Exposure vs Median")

Exposure vs Median

| Code | Count | Label | Percent |
| --- | --- | --- | --- |
| 0 | 95 | Below Median | 67.9 |
| 1 | 45 | Above Median | 32.1 |

# --- Composite: Practice Education Score ---  
cat("### Composite Practice - Education Score\n")

## ### Composite Practice - Education Score

compFUN(df, "PRACTICE\_EDUCATION\_SCORE") %>% kable(caption = "Education Engagement (0–3)")

Education Engagement (0–3)

| Mean | Median | SD | Range | N |
| --- | --- | --- | --- | --- |
| 2.292857 | 2 | 0.5158834 | 1–3 | 140 |

compFUN(df, "PRACTICE\_EDUCATION\_NORM") %>% kable(caption = "Education Engagement (Normalized 0–1)")

Education Engagement (Normalized 0–1)

| Mean | Median | SD | Range | N |
| --- | --- | --- | --- | --- |
| 0.7642857 | 0.6666667 | 0.1719611 | 0.333333333333333–1 | 140 |

binFUN(df, "PRACTICE\_AVG", labels = c("Below Avg", "Above Avg")) %>% kable(caption = "Education vs Average")

Education vs Average

| Code | Count | Label | Percent |
| --- | --- | --- | --- |
| 0 | 95 | Below Avg | 67.9 |
| 1 | 45 | Above Avg | 32.1 |

binFUN(df, "PRACTICE\_MED", labels = c("Below Median", "Above Median")) %>% kable(caption = "Education vs Median")

Education vs Median

| Code | Count | Label | Percent |
| --- | --- | --- | --- |
| 0 | 95 | Below Median | 67.9 |
| 1 | 45 | Above Median | 32.1 |

# --- Trust in Info Sources (Optional) ---  
cat("### Source of Wildlife Health Information\n")

## ### Source of Wildlife Health Information

binFUN(df, "SOURCE\_TRUST\_BIN", labels = c("Less Reliability", "More Reliability")) %>%   
 kable(caption = "Trusted > Untrusted Sources")

Trusted > Untrusted Sources

| Code | Count | Label | Percent |
| --- | --- | --- | --- |
| 0 | 35 | Less Reliability | 25 |
| 1 | 105 | More Reliability | 75 |

# 3 Chi-squared / Cramers V

require(rcompanion)  
require(kableExtra)  
require(officer)  
require(flextable)

#### 3.0.0.1 Groups

binary\_vars <- names(df)[sapply(df, function(x) is.factor(x) || (is.numeric(x) && length(unique(na.omit(x))) <= 2))]  
binary\_vars

## [1] "RACE\_BIN" "INCOME\_BIN" "GENDER\_BIN"   
## [4] "RESIDENT\_BIN" "AGE\_BIN" "SELFTITLE\_BIN"   
## [7] "LICENSE\_BIN" "BIOTIME\_BIN" "EDUCATION\_BIN"   
## [10] "DEGREE\_BIN" "TWS\_BIN" "COURSE\_BIN"   
## [13] "COURSETIME\_BIN" "DEMO\_EDU\_AVG" "DEMO\_EDU\_MED"   
## [16] "DEMO\_EXP\_AVG" "DEMO\_EXP\_MED" "PIGS\_BINK"   
## [19] "BRUCE\_BINK" "CWD\_BINK" "FLUAL\_BINK"   
## [22] "FLU\_BINK" "COVID\_BINK" "COVIDSPILL\_BINK"   
## [25] "RABIESAL\_BINK" "RABIES\_BINK" "TURKEY\_BINK"   
## [28] "KNOWLEDGE\_AVG" "KNOWLEDGE\_MED" "PIGS\_BINC"   
## [31] "BRUCE\_BINC" "CWD\_BINC" "FLUAL\_BINC"   
## [34] "FLU\_BINC" "COVID\_BINC" "COVIDSPILL\_BINC"   
## [37] "RABIESAL\_BINC" "RABIES\_BINC" "TURKEY\_BINC"   
## [40] "CONFIDENCE\_AVG" "CONFIDENCE\_MED" "CONTROL\_AVG"   
## [43] "CONTROL\_MED" "MISINFO\_AVG" "MISINFO\_MED"   
## [46] "CONCERN\_AVG" "CONCERN\_MED" "EDUCATION\_AVG"   
## [49] "EDUCATION\_MED" "REVERSE\_AVG" "REVERSE\_MED"   
## [52] "DIRECT\_AVG" "DIRECT\_MED" "TOPIC\_COUNT"   
## [55] "COLLECT\_BIN" "HANDLE\_BIN" "PPE\_BIN"   
## [58] "ACCESS\_BIN" "CONTACT\_BIN" "INTEREST\_BIN"   
## [61] "FIELD\_BIN\_MED" "FIELD\_BIN\_50" "STATE\_BIN"   
## [64] "PPETIME\_BIN" "FREEINFO\_BIN\_INPERSON" "FREEINFO\_BIN\_VIRTUAL"   
## [67] "FREEINFO\_BIN\_OTHER" "TOPIC\_BIN\_RABIES" "TOPIC\_BIN\_FLU"   
## [70] "TOPIC\_BIN\_LEPTO" "TOPIC\_BIN\_RR" "TOPIC\_BIN\_VECTOR"   
## [73] "TOPIC\_BIN\_CWD" "TOPIC\_BIN\_COVID" "TOPIC\_BIN\_ONEHEALTH"   
## [76] "TOPIC\_BIN\_OTHER" "TOPIC\_BREADTH\_BIN" "SOURCE\_BIN\_FAMILY"   
## [79] "SOURCE\_BIN\_AGENCY" "SOURCE\_BIN\_ACADEMIC" "SOURCE\_BIN\_SOCIAL"   
## [82] "SOURCE\_BIN\_NEWS" "SOURCE\_BIN\_CONFERENCES" "SOURCE\_BIN\_NONE"   
## [85] "SOURCE\_BIN\_OTHER" "SOURCE\_TRUST\_BIN" "PRACTICE\_AVG"   
## [88] "PRACTICE\_MED"

# Demographics -------------------------------------------------------------------  
DEMvar <- c("RACE\_BIN", "INCOME\_BIN", "GENDER\_BIN", "AGE\_BIN", "RESIDENT\_BIN", "STATE\_BIN")  
IDvar <- c("SELFTITLE\_BIN", "LICENSE\_BIN")   
EDUvar <- c("EDUCATION\_BIN", "DEGREE\_BIN", "DEMO\_EDU\_MED", "DEMO\_EDU\_AVG")   
EXPvar <- c("TWS\_BIN", "COURSE\_BIN", "COURSETIME\_BIN", "BIOTIME\_BIN", "DEMO\_EXP\_MED", "DEMO\_EXP\_AVG")  
  
# Knowledge ----------------------------------------------------------------------  
KNOWvar <- c("PIGS\_BINK", "BRUCE\_BINK", "CWD\_BINK", "FLUAL\_BINK", "FLU\_BINK",  
 "COVID\_BINK", "COVIDSPILL\_BINK", "RABIESAL\_BINK", "RABIES\_BINK", "TURKEY\_BINK")   
KNOWbin <- c("KNOWLEDGE\_MED", "KNOWLEDGE\_AVG")   
CONFvar <- c("PIGS\_BINC", "BRUCE\_BINC", "CWD\_BINC", "FLUAL\_BINC", "FLU\_BINC",  
 "COVID\_BINC", "COVIDSPILL\_BINC", "RABIESAL\_BINC", "RABIES\_BINC", "TURKEY\_BINC")   
CONFbin <- c("CONFIDENCE\_MED", "CONFIDENCE\_AVG")   
  
# Attitudes ----------------------------------------------------------------------  
TUDEbin <- c("CONTROL\_AVG", "CONTROL\_MED", "MISINFO\_AVG", "MISINFO\_MED", "CONCERN\_AVG", "CONCERN\_MED",  
 "EDUCATION\_AVG", "EDUCATION\_MED", "REVERSE\_AVG", "REVERSE\_MED", "DIRECT\_AVG", "DIRECT\_MED")   
  
# Practices --------------------------------------------------------------  
PRACvar <- c("CONTACT\_BIN", "FIELD\_BIN\_MED", "FIELD\_BIN\_50", "COLLECT\_BIN", "HANDLE\_BIN")  
PRACbin <- c("PRACTICE\_AVG", "PRACTICE\_MED")   
PPEvar <- c("PPE\_BIN", "PPETIME\_BIN")   
SOURCE <- c("SOURCE\_TRUST\_BIN")

#### 3.0.0.2 Comparisons

results <- list(  
 # Demographics x Knowledge  
 demo\_know = extract\_summary(run\_chi\_batch(df, DEMvar, KNOWbin)),  
 # Demographics x Confidence  
 demo\_conf = extract\_summary(run\_chi\_batch(df, DEMvar, CONFbin)),  
 # Education x Knowledge  
 edu\_know = extract\_summary(run\_chi\_batch(df, EDUvar, KNOWbin)),  
 # Education x Confidence  
 edu\_conf = extract\_summary(run\_chi\_batch(df, EDUvar, CONFbin)),  
 # Experience x Knowledge  
 exp\_know = extract\_summary(run\_chi\_batch(df, EXPvar, KNOWbin)),  
 # Experience x Confidence  
 exp\_conf = extract\_summary(run\_chi\_batch(df, EXPvar, CONFbin)),  
 # Identity x Knowledge  
 id\_know = extract\_summary(run\_chi\_batch(df, IDvar, KNOWbin)),  
 # Identity x Confidence  
 id\_conf = extract\_summary(run\_chi\_batch(df, IDvar, CONFbin)),  
 # Knowledge x Confidence (Cross-variable consistency)  
 know\_conf = extract\_summary(run\_chi\_batch(df, KNOWbin, CONFbin)),  
 # Attitudes x Knowledge  
 att\_know = extract\_summary(run\_chi\_batch(df, TUDEbin, KNOWbin)),  
 # Attitudes x Confidence  
 att\_conf = extract\_summary(run\_chi\_batch(df, TUDEbin, CONFbin)),  
 # Practices x Knowledge  
 prac\_know = extract\_summary(run\_chi\_batch(df, PRACvar, KNOWbin)),  
 # Practices x Confidence  
 prac\_conf = extract\_summary(run\_chi\_batch(df, PRACvar, CONFbin)),  
 # Practice Scores x Knowledge  
 pracsco\_know = extract\_summary(run\_chi\_batch(df, PRACbin, KNOWbin)),  
 # Practice Scores x Confidence  
 pracsco\_conf = extract\_summary(run\_chi\_batch(df, PRACbin, CONFbin)),  
 # PPE Usage x Practices  
 ppe\_prac = extract\_summary(run\_chi\_batch(df, PPEvar, PRACvar)),  
 # PPE Usage x Practice Scores  
 ppe\_pracsco = extract\_summary(run\_chi\_batch(df, PPEvar, PRACbin)),  
 # Sources x Knowledge  
 sources\_know = extract\_summary(run\_chi\_batch(df, SOURCE, KNOWvar)))  
  
str(results, max.level = 1)

## List of 18  
## $ demo\_know :'data.frame': 10 obs. of 7 variables:  
## $ demo\_conf :'data.frame': 10 obs. of 7 variables:  
## $ edu\_know :'data.frame': 6 obs. of 7 variables:  
## $ edu\_conf :'data.frame': 6 obs. of 7 variables:  
## $ exp\_know :'data.frame': 12 obs. of 7 variables:  
## $ exp\_conf :'data.frame': 12 obs. of 7 variables:  
## $ id\_know :'data.frame': 4 obs. of 7 variables:  
## $ id\_conf :'data.frame': 4 obs. of 7 variables:  
## $ know\_conf :'data.frame': 4 obs. of 7 variables:  
## $ att\_know :'data.frame': 24 obs. of 7 variables:  
## $ att\_conf :'data.frame': 24 obs. of 7 variables:  
## $ prac\_know :'data.frame': 10 obs. of 7 variables:  
## $ prac\_conf :'data.frame': 10 obs. of 7 variables:  
## $ pracsco\_know:'data.frame': 4 obs. of 7 variables:  
## $ pracsco\_conf:'data.frame': 4 obs. of 7 variables:  
## $ ppe\_prac :'data.frame': 5 obs. of 7 variables:  
## $ ppe\_pracsco :'data.frame': 2 obs. of 7 variables:  
## $ sources\_know:'data.frame': 10 obs. of 7 variables:

results

## $demo\_know  
## Variable\_Pair Chi\_Square df p\_value  
## RACE\_BIN\_x\_KNOWLEDGE\_MED RACE\_BIN\_x\_KNOWLEDGE\_MED 0.000000 1 1.00000000  
## RACE\_BIN\_x\_KNOWLEDGE\_AVG RACE\_BIN\_x\_KNOWLEDGE\_AVG 0.000000 1 1.00000000  
## INCOME\_BIN\_x\_KNOWLEDGE\_MED INCOME\_BIN\_x\_KNOWLEDGE\_MED 3.701923 1 0.05434979  
## INCOME\_BIN\_x\_KNOWLEDGE\_AVG INCOME\_BIN\_x\_KNOWLEDGE\_AVG 3.701923 1 0.05434979  
## GENDER\_BIN\_x\_KNOWLEDGE\_MED GENDER\_BIN\_x\_KNOWLEDGE\_MED 1.336609 1 0.24763280  
## GENDER\_BIN\_x\_KNOWLEDGE\_AVG GENDER\_BIN\_x\_KNOWLEDGE\_AVG 1.336609 1 0.24763280  
## AGE\_BIN\_x\_KNOWLEDGE\_MED AGE\_BIN\_x\_KNOWLEDGE\_MED 2.314286 1 0.12819017  
## AGE\_BIN\_x\_KNOWLEDGE\_AVG AGE\_BIN\_x\_KNOWLEDGE\_AVG 2.314286 1 0.12819017  
## STATE\_BIN\_x\_KNOWLEDGE\_MED STATE\_BIN\_x\_KNOWLEDGE\_MED 3.484166 1 0.06195858  
## STATE\_BIN\_x\_KNOWLEDGE\_AVG STATE\_BIN\_x\_KNOWLEDGE\_AVG 3.484166 1 0.06195858  
## CramerV Effect\_Size Significant  
## RACE\_BIN\_x\_KNOWLEDGE\_MED 0.0000 Negligible FALSE  
## RACE\_BIN\_x\_KNOWLEDGE\_AVG 0.0000 Negligible FALSE  
## INCOME\_BIN\_x\_KNOWLEDGE\_MED 0.1774 Small FALSE  
## INCOME\_BIN\_x\_KNOWLEDGE\_AVG 0.1774 Small FALSE  
## GENDER\_BIN\_x\_KNOWLEDGE\_MED 0.1157 Small FALSE  
## GENDER\_BIN\_x\_KNOWLEDGE\_AVG 0.1157 Small FALSE  
## AGE\_BIN\_x\_KNOWLEDGE\_MED 0.1429 Small FALSE  
## AGE\_BIN\_x\_KNOWLEDGE\_AVG 0.1429 Small FALSE  
## STATE\_BIN\_x\_KNOWLEDGE\_MED 0.2994 Small FALSE  
## STATE\_BIN\_x\_KNOWLEDGE\_AVG 0.2994 Small FALSE  
##   
## $demo\_conf  
## Variable\_Pair Chi\_Square df  
## RACE\_BIN\_x\_CONFIDENCE\_MED RACE\_BIN\_x\_CONFIDENCE\_MED 9.780917e-32 1  
## RACE\_BIN\_x\_CONFIDENCE\_AVG RACE\_BIN\_x\_CONFIDENCE\_AVG 9.780917e-32 1  
## INCOME\_BIN\_x\_CONFIDENCE\_MED INCOME\_BIN\_x\_CONFIDENCE\_MED 5.581491e+00 1  
## INCOME\_BIN\_x\_CONFIDENCE\_AVG INCOME\_BIN\_x\_CONFIDENCE\_AVG 5.581491e+00 1  
## GENDER\_BIN\_x\_CONFIDENCE\_MED GENDER\_BIN\_x\_CONFIDENCE\_MED 1.974843e+00 1  
## GENDER\_BIN\_x\_CONFIDENCE\_AVG GENDER\_BIN\_x\_CONFIDENCE\_AVG 1.974843e+00 1  
## AGE\_BIN\_x\_CONFIDENCE\_MED AGE\_BIN\_x\_CONFIDENCE\_MED 1.410362e+00 1  
## AGE\_BIN\_x\_CONFIDENCE\_AVG AGE\_BIN\_x\_CONFIDENCE\_AVG 1.410362e+00 1  
## STATE\_BIN\_x\_CONFIDENCE\_MED STATE\_BIN\_x\_CONFIDENCE\_MED 4.312824e+00 1  
## STATE\_BIN\_x\_CONFIDENCE\_AVG STATE\_BIN\_x\_CONFIDENCE\_AVG 4.312824e+00 1  
## p\_value CramerV Effect\_Size Significant  
## RACE\_BIN\_x\_CONFIDENCE\_MED 1.00000000 0.02386 Negligible FALSE  
## RACE\_BIN\_x\_CONFIDENCE\_AVG 1.00000000 0.02386 Negligible FALSE  
## INCOME\_BIN\_x\_CONFIDENCE\_MED 0.01815126 0.21450 Small TRUE  
## INCOME\_BIN\_x\_CONFIDENCE\_AVG 0.01815126 0.21450 Small TRUE  
## GENDER\_BIN\_x\_CONFIDENCE\_MED 0.15993479 0.13710 Small FALSE  
## GENDER\_BIN\_x\_CONFIDENCE\_AVG 0.15993479 0.13710 Small FALSE  
## AGE\_BIN\_x\_CONFIDENCE\_MED 0.23499633 0.11470 Small FALSE  
## AGE\_BIN\_x\_CONFIDENCE\_AVG 0.23499633 0.11470 Small FALSE  
## STATE\_BIN\_x\_CONFIDENCE\_MED 0.03782612 0.32870 Moderate TRUE  
## STATE\_BIN\_x\_CONFIDENCE\_AVG 0.03782612 0.32870 Moderate TRUE  
##   
## $edu\_know  
## Variable\_Pair Chi\_Square df  
## EDUCATION\_BIN\_x\_KNOWLEDGE\_MED EDUCATION\_BIN\_x\_KNOWLEDGE\_MED 5.921295 1  
## EDUCATION\_BIN\_x\_KNOWLEDGE\_AVG EDUCATION\_BIN\_x\_KNOWLEDGE\_AVG 5.921295 1  
## DEGREE\_BIN\_x\_KNOWLEDGE\_MED DEGREE\_BIN\_x\_KNOWLEDGE\_MED 7.169697 1  
## DEGREE\_BIN\_x\_KNOWLEDGE\_AVG DEGREE\_BIN\_x\_KNOWLEDGE\_AVG 7.169697 1  
## DEMO\_EDU\_AVG\_x\_KNOWLEDGE\_MED DEMO\_EDU\_AVG\_x\_KNOWLEDGE\_MED 7.169697 1  
## DEMO\_EDU\_AVG\_x\_KNOWLEDGE\_AVG DEMO\_EDU\_AVG\_x\_KNOWLEDGE\_AVG 7.169697 1  
## p\_value CramerV Effect\_Size Significant  
## EDUCATION\_BIN\_x\_KNOWLEDGE\_MED 0.01495896 0.2248 Small TRUE  
## EDUCATION\_BIN\_x\_KNOWLEDGE\_AVG 0.01495896 0.2248 Small TRUE  
## DEGREE\_BIN\_x\_KNOWLEDGE\_MED 0.00741453 0.2437 Small TRUE  
## DEGREE\_BIN\_x\_KNOWLEDGE\_AVG 0.00741453 0.2437 Small TRUE  
## DEMO\_EDU\_AVG\_x\_KNOWLEDGE\_MED 0.00741453 0.2437 Small TRUE  
## DEMO\_EDU\_AVG\_x\_KNOWLEDGE\_AVG 0.00741453 0.2437 Small TRUE  
##   
## $edu\_conf  
## Variable\_Pair Chi\_Square df  
## EDUCATION\_BIN\_x\_CONFIDENCE\_MED EDUCATION\_BIN\_x\_CONFIDENCE\_MED 6.237301 1  
## EDUCATION\_BIN\_x\_CONFIDENCE\_AVG EDUCATION\_BIN\_x\_CONFIDENCE\_AVG 6.237301 1  
## DEGREE\_BIN\_x\_CONFIDENCE\_MED DEGREE\_BIN\_x\_CONFIDENCE\_MED 7.871686 1  
## DEGREE\_BIN\_x\_CONFIDENCE\_AVG DEGREE\_BIN\_x\_CONFIDENCE\_AVG 7.871686 1  
## DEMO\_EDU\_AVG\_x\_CONFIDENCE\_MED DEMO\_EDU\_AVG\_x\_CONFIDENCE\_MED 7.871686 1  
## DEMO\_EDU\_AVG\_x\_CONFIDENCE\_AVG DEMO\_EDU\_AVG\_x\_CONFIDENCE\_AVG 7.871686 1  
## p\_value CramerV Effect\_Size Significant  
## EDUCATION\_BIN\_x\_CONFIDENCE\_MED 0.012508699 0.2304 Small TRUE  
## EDUCATION\_BIN\_x\_CONFIDENCE\_AVG 0.012508699 0.2304 Small TRUE  
## DEGREE\_BIN\_x\_CONFIDENCE\_MED 0.005021482 0.2546 Small TRUE  
## DEGREE\_BIN\_x\_CONFIDENCE\_AVG 0.005021482 0.2546 Small TRUE  
## DEMO\_EDU\_AVG\_x\_CONFIDENCE\_MED 0.005021482 0.2546 Small TRUE  
## DEMO\_EDU\_AVG\_x\_CONFIDENCE\_AVG 0.005021482 0.2546 Small TRUE  
##   
## $exp\_know  
## Variable\_Pair Chi\_Square df  
## TWS\_BIN\_x\_KNOWLEDGE\_MED TWS\_BIN\_x\_KNOWLEDGE\_MED 0.4525862 1  
## TWS\_BIN\_x\_KNOWLEDGE\_AVG TWS\_BIN\_x\_KNOWLEDGE\_AVG 0.4525862 1  
## COURSE\_BIN\_x\_KNOWLEDGE\_MED COURSE\_BIN\_x\_KNOWLEDGE\_MED 5.0297619 1  
## COURSE\_BIN\_x\_KNOWLEDGE\_AVG COURSE\_BIN\_x\_KNOWLEDGE\_AVG 5.0297619 1  
## COURSETIME\_BIN\_x\_KNOWLEDGE\_MED COURSETIME\_BIN\_x\_KNOWLEDGE\_MED 2.1026820 1  
## COURSETIME\_BIN\_x\_KNOWLEDGE\_AVG COURSETIME\_BIN\_x\_KNOWLEDGE\_AVG 2.1026820 1  
## BIOTIME\_BIN\_x\_KNOWLEDGE\_MED BIOTIME\_BIN\_x\_KNOWLEDGE\_MED 8.0376766 1  
## BIOTIME\_BIN\_x\_KNOWLEDGE\_AVG BIOTIME\_BIN\_x\_KNOWLEDGE\_AVG 8.0376766 1  
## DEMO\_EXP\_MED\_x\_KNOWLEDGE\_MED DEMO\_EXP\_MED\_x\_KNOWLEDGE\_MED 7.8960123 1  
## DEMO\_EXP\_MED\_x\_KNOWLEDGE\_AVG DEMO\_EXP\_MED\_x\_KNOWLEDGE\_AVG 7.8960123 1  
## DEMO\_EXP\_AVG\_x\_KNOWLEDGE\_MED DEMO\_EXP\_AVG\_x\_KNOWLEDGE\_MED 7.8960123 1  
## DEMO\_EXP\_AVG\_x\_KNOWLEDGE\_AVG DEMO\_EXP\_AVG\_x\_KNOWLEDGE\_AVG 7.8960123 1  
## p\_value CramerV Effect\_Size Significant  
## TWS\_BIN\_x\_KNOWLEDGE\_MED 0.501109358 0.07581 Negligible FALSE  
## TWS\_BIN\_x\_KNOWLEDGE\_AVG 0.501109358 0.07581 Negligible FALSE  
## COURSE\_BIN\_x\_KNOWLEDGE\_MED 0.024915323 0.20410 Small TRUE  
## COURSE\_BIN\_x\_KNOWLEDGE\_AVG 0.024915323 0.20410 Small TRUE  
## COURSETIME\_BIN\_x\_KNOWLEDGE\_MED 0.147041020 0.23070 Small FALSE  
## COURSETIME\_BIN\_x\_KNOWLEDGE\_AVG 0.147041020 0.23070 Small FALSE  
## BIOTIME\_BIN\_x\_KNOWLEDGE\_MED 0.004581426 0.25460 Small TRUE  
## BIOTIME\_BIN\_x\_KNOWLEDGE\_AVG 0.004581426 0.25460 Small TRUE  
## DEMO\_EXP\_MED\_x\_KNOWLEDGE\_MED 0.004954390 0.25230 Small TRUE  
## DEMO\_EXP\_MED\_x\_KNOWLEDGE\_AVG 0.004954390 0.25230 Small TRUE  
## DEMO\_EXP\_AVG\_x\_KNOWLEDGE\_MED 0.004954390 0.25230 Small TRUE  
## DEMO\_EXP\_AVG\_x\_KNOWLEDGE\_AVG 0.004954390 0.25230 Small TRUE  
##   
## $exp\_conf  
## Variable\_Pair Chi\_Square df  
## TWS\_BIN\_x\_CONFIDENCE\_MED TWS\_BIN\_x\_CONFIDENCE\_MED 4.384549e-31 1  
## TWS\_BIN\_x\_CONFIDENCE\_AVG TWS\_BIN\_x\_CONFIDENCE\_AVG 4.384549e-31 1  
## COURSE\_BIN\_x\_CONFIDENCE\_MED COURSE\_BIN\_x\_CONFIDENCE\_MED 7.868524e+00 1  
## COURSE\_BIN\_x\_CONFIDENCE\_AVG COURSE\_BIN\_x\_CONFIDENCE\_AVG 7.868524e+00 1  
## COURSETIME\_BIN\_x\_CONFIDENCE\_MED COURSETIME\_BIN\_x\_CONFIDENCE\_MED 2.459612e+00 1  
## COURSETIME\_BIN\_x\_CONFIDENCE\_AVG COURSETIME\_BIN\_x\_CONFIDENCE\_AVG 2.459612e+00 1  
## BIOTIME\_BIN\_x\_CONFIDENCE\_MED BIOTIME\_BIN\_x\_CONFIDENCE\_MED 1.002151e+01 1  
## BIOTIME\_BIN\_x\_CONFIDENCE\_AVG BIOTIME\_BIN\_x\_CONFIDENCE\_AVG 1.002151e+01 1  
## DEMO\_EXP\_MED\_x\_CONFIDENCE\_MED DEMO\_EXP\_MED\_x\_CONFIDENCE\_MED 5.771265e+00 1  
## DEMO\_EXP\_MED\_x\_CONFIDENCE\_AVG DEMO\_EXP\_MED\_x\_CONFIDENCE\_AVG 5.771265e+00 1  
## DEMO\_EXP\_AVG\_x\_CONFIDENCE\_MED DEMO\_EXP\_AVG\_x\_CONFIDENCE\_MED 5.771265e+00 1  
## DEMO\_EXP\_AVG\_x\_CONFIDENCE\_AVG DEMO\_EXP\_AVG\_x\_CONFIDENCE\_AVG 5.771265e+00 1  
## p\_value CramerV Effect\_Size Significant  
## TWS\_BIN\_x\_CONFIDENCE\_MED 1.000000000 0.001087 Negligible FALSE  
## TWS\_BIN\_x\_CONFIDENCE\_AVG 1.000000000 0.001087 Negligible FALSE  
## COURSE\_BIN\_x\_CONFIDENCE\_MED 0.005030270 0.251700 Small TRUE  
## COURSE\_BIN\_x\_CONFIDENCE\_AVG 0.005030270 0.251700 Small TRUE  
## COURSETIME\_BIN\_x\_CONFIDENCE\_MED 0.116807621 0.248400 Small FALSE  
## COURSETIME\_BIN\_x\_CONFIDENCE\_AVG 0.116807621 0.248400 Small FALSE  
## BIOTIME\_BIN\_x\_CONFIDENCE\_MED 0.001547227 0.282600 Small TRUE  
## BIOTIME\_BIN\_x\_CONFIDENCE\_AVG 0.001547227 0.282600 Small TRUE  
## DEMO\_EXP\_MED\_x\_CONFIDENCE\_MED 0.016290302 0.217900 Small TRUE  
## DEMO\_EXP\_MED\_x\_CONFIDENCE\_AVG 0.016290302 0.217900 Small TRUE  
## DEMO\_EXP\_AVG\_x\_CONFIDENCE\_MED 0.016290302 0.217900 Small TRUE  
## DEMO\_EXP\_AVG\_x\_CONFIDENCE\_AVG 0.016290302 0.217900 Small TRUE  
##   
## $id\_know  
## Variable\_Pair Chi\_Square df  
## SELFTITLE\_BIN\_x\_KNOWLEDGE\_MED SELFTITLE\_BIN\_x\_KNOWLEDGE\_MED 6.846065 1  
## SELFTITLE\_BIN\_x\_KNOWLEDGE\_AVG SELFTITLE\_BIN\_x\_KNOWLEDGE\_AVG 6.846065 1  
## LICENSE\_BIN\_x\_KNOWLEDGE\_MED LICENSE\_BIN\_x\_KNOWLEDGE\_MED 9.098756 1  
## LICENSE\_BIN\_x\_KNOWLEDGE\_AVG LICENSE\_BIN\_x\_KNOWLEDGE\_AVG 9.098756 1  
## p\_value CramerV Effect\_Size Significant  
## SELFTITLE\_BIN\_x\_KNOWLEDGE\_MED 0.008883673 0.2381 Small TRUE  
## SELFTITLE\_BIN\_x\_KNOWLEDGE\_AVG 0.008883673 0.2381 Small TRUE  
## LICENSE\_BIN\_x\_KNOWLEDGE\_MED 0.002557834 0.2709 Small TRUE  
## LICENSE\_BIN\_x\_KNOWLEDGE\_AVG 0.002557834 0.2709 Small TRUE  
##   
## $id\_conf  
## Variable\_Pair Chi\_Square df  
## SELFTITLE\_BIN\_x\_CONFIDENCE\_MED SELFTITLE\_BIN\_x\_CONFIDENCE\_MED 1.345900 1  
## SELFTITLE\_BIN\_x\_CONFIDENCE\_AVG SELFTITLE\_BIN\_x\_CONFIDENCE\_AVG 1.345900 1  
## LICENSE\_BIN\_x\_CONFIDENCE\_MED LICENSE\_BIN\_x\_CONFIDENCE\_MED 8.428631 1  
## LICENSE\_BIN\_x\_CONFIDENCE\_AVG LICENSE\_BIN\_x\_CONFIDENCE\_AVG 8.428631 1  
## p\_value CramerV Effect\_Size Significant  
## SELFTITLE\_BIN\_x\_CONFIDENCE\_MED 0.245996139 0.1151 Small FALSE  
## SELFTITLE\_BIN\_x\_CONFIDENCE\_AVG 0.245996139 0.1151 Small FALSE  
## LICENSE\_BIN\_x\_CONFIDENCE\_MED 0.003693583 0.2614 Small TRUE  
## LICENSE\_BIN\_x\_CONFIDENCE\_AVG 0.003693583 0.2614 Small TRUE  
##   
## $know\_conf  
## Variable\_Pair Chi\_Square df  
## KNOWLEDGE\_MED\_x\_CONFIDENCE\_MED KNOWLEDGE\_MED\_x\_CONFIDENCE\_MED 74.86431 1  
## KNOWLEDGE\_MED\_x\_CONFIDENCE\_AVG KNOWLEDGE\_MED\_x\_CONFIDENCE\_AVG 74.86431 1  
## KNOWLEDGE\_AVG\_x\_CONFIDENCE\_MED KNOWLEDGE\_AVG\_x\_CONFIDENCE\_MED 74.86431 1  
## KNOWLEDGE\_AVG\_x\_CONFIDENCE\_AVG KNOWLEDGE\_AVG\_x\_CONFIDENCE\_AVG 74.86431 1  
## p\_value CramerV Effect\_Size Significant  
## KNOWLEDGE\_MED\_x\_CONFIDENCE\_MED 5.04203e-18 0.7456 Large TRUE  
## KNOWLEDGE\_MED\_x\_CONFIDENCE\_AVG 5.04203e-18 0.7456 Large TRUE  
## KNOWLEDGE\_AVG\_x\_CONFIDENCE\_MED 5.04203e-18 0.7456 Large TRUE  
## KNOWLEDGE\_AVG\_x\_CONFIDENCE\_AVG 5.04203e-18 0.7456 Large TRUE  
##   
## $att\_know  
## Variable\_Pair Chi\_Square df  
## CONTROL\_AVG\_x\_KNOWLEDGE\_MED CONTROL\_AVG\_x\_KNOWLEDGE\_MED 0.4594872 1  
## CONTROL\_AVG\_x\_KNOWLEDGE\_AVG CONTROL\_AVG\_x\_KNOWLEDGE\_AVG 0.4594872 1  
## CONTROL\_MED\_x\_KNOWLEDGE\_MED CONTROL\_MED\_x\_KNOWLEDGE\_MED 0.4594872 1  
## CONTROL\_MED\_x\_KNOWLEDGE\_AVG CONTROL\_MED\_x\_KNOWLEDGE\_AVG 0.4594872 1  
## MISINFO\_AVG\_x\_KNOWLEDGE\_MED MISINFO\_AVG\_x\_KNOWLEDGE\_MED 11.6206682 1  
## MISINFO\_AVG\_x\_KNOWLEDGE\_AVG MISINFO\_AVG\_x\_KNOWLEDGE\_AVG 11.6206682 1  
## MISINFO\_MED\_x\_KNOWLEDGE\_MED MISINFO\_MED\_x\_KNOWLEDGE\_MED 19.8143116 1  
## MISINFO\_MED\_x\_KNOWLEDGE\_AVG MISINFO\_MED\_x\_KNOWLEDGE\_AVG 19.8143116 1  
## CONCERN\_AVG\_x\_KNOWLEDGE\_MED CONCERN\_AVG\_x\_KNOWLEDGE\_MED 4.0516735 1  
## CONCERN\_AVG\_x\_KNOWLEDGE\_AVG CONCERN\_AVG\_x\_KNOWLEDGE\_AVG 4.0516735 1  
## CONCERN\_MED\_x\_KNOWLEDGE\_MED CONCERN\_MED\_x\_KNOWLEDGE\_MED 5.2470357 1  
## CONCERN\_MED\_x\_KNOWLEDGE\_AVG CONCERN\_MED\_x\_KNOWLEDGE\_AVG 5.2470357 1  
## EDUCATION\_AVG\_x\_KNOWLEDGE\_MED EDUCATION\_AVG\_x\_KNOWLEDGE\_MED 1.2090337 1  
## EDUCATION\_AVG\_x\_KNOWLEDGE\_AVG EDUCATION\_AVG\_x\_KNOWLEDGE\_AVG 1.2090337 1  
## EDUCATION\_MED\_x\_KNOWLEDGE\_MED EDUCATION\_MED\_x\_KNOWLEDGE\_MED 1.2090337 1  
## EDUCATION\_MED\_x\_KNOWLEDGE\_AVG EDUCATION\_MED\_x\_KNOWLEDGE\_AVG 1.2090337 1  
## REVERSE\_AVG\_x\_KNOWLEDGE\_MED REVERSE\_AVG\_x\_KNOWLEDGE\_MED 4.1353846 1  
## REVERSE\_AVG\_x\_KNOWLEDGE\_AVG REVERSE\_AVG\_x\_KNOWLEDGE\_AVG 4.1353846 1  
## REVERSE\_MED\_x\_KNOWLEDGE\_MED REVERSE\_MED\_x\_KNOWLEDGE\_MED 4.1353846 1  
## REVERSE\_MED\_x\_KNOWLEDGE\_AVG REVERSE\_MED\_x\_KNOWLEDGE\_AVG 4.1353846 1  
## DIRECT\_AVG\_x\_KNOWLEDGE\_MED DIRECT\_AVG\_x\_KNOWLEDGE\_MED 2.8717949 1  
## DIRECT\_AVG\_x\_KNOWLEDGE\_AVG DIRECT\_AVG\_x\_KNOWLEDGE\_AVG 2.8717949 1  
## DIRECT\_MED\_x\_KNOWLEDGE\_MED DIRECT\_MED\_x\_KNOWLEDGE\_MED 2.8717949 1  
## DIRECT\_MED\_x\_KNOWLEDGE\_AVG DIRECT\_MED\_x\_KNOWLEDGE\_AVG 2.8717949 1  
## p\_value CramerV Effect\_Size Significant  
## CONTROL\_AVG\_x\_KNOWLEDGE\_MED 4.978637e-01 0.07161 Negligible FALSE  
## CONTROL\_AVG\_x\_KNOWLEDGE\_AVG 4.978637e-01 0.07161 Negligible FALSE  
## CONTROL\_MED\_x\_KNOWLEDGE\_MED 4.978637e-01 0.07161 Negligible FALSE  
## CONTROL\_MED\_x\_KNOWLEDGE\_AVG 4.978637e-01 0.07161 Negligible FALSE  
## MISINFO\_AVG\_x\_KNOWLEDGE\_MED 6.522297e-04 0.30250 Moderate TRUE  
## MISINFO\_AVG\_x\_KNOWLEDGE\_AVG 6.522297e-04 0.30250 Moderate TRUE  
## MISINFO\_MED\_x\_KNOWLEDGE\_MED 8.534129e-06 0.39130 Moderate TRUE  
## MISINFO\_MED\_x\_KNOWLEDGE\_AVG 8.534129e-06 0.39130 Moderate TRUE  
## CONCERN\_AVG\_x\_KNOWLEDGE\_MED 4.412758e-02 0.18540 Small TRUE  
## CONCERN\_AVG\_x\_KNOWLEDGE\_AVG 4.412758e-02 0.18540 Small TRUE  
## CONCERN\_MED\_x\_KNOWLEDGE\_MED 2.198419e-02 0.20870 Small TRUE  
## CONCERN\_MED\_x\_KNOWLEDGE\_AVG 2.198419e-02 0.20870 Small TRUE  
## EDUCATION\_AVG\_x\_KNOWLEDGE\_MED 2.715236e-01 0.10770 Small FALSE  
## EDUCATION\_AVG\_x\_KNOWLEDGE\_AVG 2.715236e-01 0.10770 Small FALSE  
## EDUCATION\_MED\_x\_KNOWLEDGE\_MED 2.715236e-01 0.10770 Small FALSE  
## EDUCATION\_MED\_x\_KNOWLEDGE\_AVG 2.715236e-01 0.10770 Small FALSE  
## REVERSE\_AVG\_x\_KNOWLEDGE\_MED 4.199552e-02 0.18620 Small TRUE  
## REVERSE\_AVG\_x\_KNOWLEDGE\_AVG 4.199552e-02 0.18620 Small TRUE  
## REVERSE\_MED\_x\_KNOWLEDGE\_MED 4.199552e-02 0.18620 Small TRUE  
## REVERSE\_MED\_x\_KNOWLEDGE\_AVG 4.199552e-02 0.18620 Small TRUE  
## DIRECT\_AVG\_x\_KNOWLEDGE\_MED 9.014429e-02 0.15750 Small FALSE  
## DIRECT\_AVG\_x\_KNOWLEDGE\_AVG 9.014429e-02 0.15750 Small FALSE  
## DIRECT\_MED\_x\_KNOWLEDGE\_MED 9.014429e-02 0.15750 Small FALSE  
## DIRECT\_MED\_x\_KNOWLEDGE\_AVG 9.014429e-02 0.15750 Small FALSE  
##   
## $att\_conf  
## Variable\_Pair Chi\_Square df  
## CONTROL\_AVG\_x\_CONFIDENCE\_MED CONTROL\_AVG\_x\_CONFIDENCE\_MED 1.195597 1  
## CONTROL\_AVG\_x\_CONFIDENCE\_AVG CONTROL\_AVG\_x\_CONFIDENCE\_AVG 1.195597 1  
## CONTROL\_MED\_x\_CONFIDENCE\_MED CONTROL\_MED\_x\_CONFIDENCE\_MED 1.195597 1  
## CONTROL\_MED\_x\_CONFIDENCE\_AVG CONTROL\_MED\_x\_CONFIDENCE\_AVG 1.195597 1  
## MISINFO\_AVG\_x\_CONFIDENCE\_MED MISINFO\_AVG\_x\_CONFIDENCE\_MED 15.791327 1  
## MISINFO\_AVG\_x\_CONFIDENCE\_AVG MISINFO\_AVG\_x\_CONFIDENCE\_AVG 15.791327 1  
## MISINFO\_MED\_x\_CONFIDENCE\_MED MISINFO\_MED\_x\_CONFIDENCE\_MED 26.648189 1  
## MISINFO\_MED\_x\_CONFIDENCE\_AVG MISINFO\_MED\_x\_CONFIDENCE\_AVG 26.648189 1  
## CONCERN\_AVG\_x\_CONFIDENCE\_MED CONCERN\_AVG\_x\_CONFIDENCE\_MED 2.112205 1  
## CONCERN\_AVG\_x\_CONFIDENCE\_AVG CONCERN\_AVG\_x\_CONFIDENCE\_AVG 2.112205 1  
## CONCERN\_MED\_x\_CONFIDENCE\_MED CONCERN\_MED\_x\_CONFIDENCE\_MED 2.876469 1  
## CONCERN\_MED\_x\_CONFIDENCE\_AVG CONCERN\_MED\_x\_CONFIDENCE\_AVG 2.876469 1  
## EDUCATION\_AVG\_x\_CONFIDENCE\_MED EDUCATION\_AVG\_x\_CONFIDENCE\_MED 2.373895 1  
## EDUCATION\_AVG\_x\_CONFIDENCE\_AVG EDUCATION\_AVG\_x\_CONFIDENCE\_AVG 2.373895 1  
## EDUCATION\_MED\_x\_CONFIDENCE\_MED EDUCATION\_MED\_x\_CONFIDENCE\_MED 2.373895 1  
## EDUCATION\_MED\_x\_CONFIDENCE\_AVG EDUCATION\_MED\_x\_CONFIDENCE\_AVG 2.373895 1  
## REVERSE\_AVG\_x\_CONFIDENCE\_MED REVERSE\_AVG\_x\_CONFIDENCE\_MED 3.146339 1  
## REVERSE\_AVG\_x\_CONFIDENCE\_AVG REVERSE\_AVG\_x\_CONFIDENCE\_AVG 3.146339 1  
## REVERSE\_MED\_x\_CONFIDENCE\_MED REVERSE\_MED\_x\_CONFIDENCE\_MED 3.146339 1  
## REVERSE\_MED\_x\_CONFIDENCE\_AVG REVERSE\_MED\_x\_CONFIDENCE\_AVG 3.146339 1  
## DIRECT\_AVG\_x\_CONFIDENCE\_MED DIRECT\_AVG\_x\_CONFIDENCE\_MED 6.022858 1  
## DIRECT\_AVG\_x\_CONFIDENCE\_AVG DIRECT\_AVG\_x\_CONFIDENCE\_AVG 6.022858 1  
## DIRECT\_MED\_x\_CONFIDENCE\_MED DIRECT\_MED\_x\_CONFIDENCE\_MED 6.022858 1  
## DIRECT\_MED\_x\_CONFIDENCE\_AVG DIRECT\_MED\_x\_CONFIDENCE\_AVG 6.022858 1  
## p\_value CramerV Effect\_Size Significant  
## CONTROL\_AVG\_x\_CONFIDENCE\_MED 2.742034e-01 0.1068 Small FALSE  
## CONTROL\_AVG\_x\_CONFIDENCE\_AVG 2.742034e-01 0.1068 Small FALSE  
## CONTROL\_MED\_x\_CONFIDENCE\_MED 2.742034e-01 0.1068 Small FALSE  
## CONTROL\_MED\_x\_CONFIDENCE\_AVG 2.742034e-01 0.1068 Small FALSE  
## MISINFO\_AVG\_x\_CONFIDENCE\_MED 7.072597e-05 0.3503 Moderate TRUE  
## MISINFO\_AVG\_x\_CONFIDENCE\_AVG 7.072597e-05 0.3503 Moderate TRUE  
## MISINFO\_MED\_x\_CONFIDENCE\_MED 2.440794e-07 0.4514 Moderate TRUE  
## MISINFO\_MED\_x\_CONFIDENCE\_AVG 2.440794e-07 0.4514 Moderate TRUE  
## CONCERN\_AVG\_x\_CONFIDENCE\_MED 1.461286e-01 0.1380 Small FALSE  
## CONCERN\_AVG\_x\_CONFIDENCE\_AVG 1.461286e-01 0.1380 Small FALSE  
## CONCERN\_MED\_x\_CONFIDENCE\_MED 8.988292e-02 0.1583 Small FALSE  
## CONCERN\_MED\_x\_CONFIDENCE\_AVG 8.988292e-02 0.1583 Small FALSE  
## EDUCATION\_AVG\_x\_CONFIDENCE\_MED 1.233788e-01 0.1452 Small FALSE  
## EDUCATION\_AVG\_x\_CONFIDENCE\_AVG 1.233788e-01 0.1452 Small FALSE  
## EDUCATION\_MED\_x\_CONFIDENCE\_MED 1.233788e-01 0.1452 Small FALSE  
## EDUCATION\_MED\_x\_CONFIDENCE\_AVG 1.233788e-01 0.1452 Small FALSE  
## REVERSE\_AVG\_x\_CONFIDENCE\_MED 7.609750e-02 0.1643 Small FALSE  
## REVERSE\_AVG\_x\_CONFIDENCE\_AVG 7.609750e-02 0.1643 Small FALSE  
## REVERSE\_MED\_x\_CONFIDENCE\_MED 7.609750e-02 0.1643 Small FALSE  
## REVERSE\_MED\_x\_CONFIDENCE\_AVG 7.609750e-02 0.1643 Small FALSE  
## DIRECT\_AVG\_x\_CONFIDENCE\_MED 1.412176e-02 0.2218 Small TRUE  
## DIRECT\_AVG\_x\_CONFIDENCE\_AVG 1.412176e-02 0.2218 Small TRUE  
## DIRECT\_MED\_x\_CONFIDENCE\_MED 1.412176e-02 0.2218 Small TRUE  
## DIRECT\_MED\_x\_CONFIDENCE\_AVG 1.412176e-02 0.2218 Small TRUE  
##   
## $prac\_know  
## Variable\_Pair Chi\_Square df  
## CONTACT\_BIN\_x\_KNOWLEDGE\_MED CONTACT\_BIN\_x\_KNOWLEDGE\_MED 1.82894468 1  
## CONTACT\_BIN\_x\_KNOWLEDGE\_AVG CONTACT\_BIN\_x\_KNOWLEDGE\_AVG 1.82894468 1  
## FIELD\_BIN\_MED\_x\_KNOWLEDGE\_MED FIELD\_BIN\_MED\_x\_KNOWLEDGE\_MED 0.02878289 1  
## FIELD\_BIN\_MED\_x\_KNOWLEDGE\_AVG FIELD\_BIN\_MED\_x\_KNOWLEDGE\_AVG 0.02878289 1  
## FIELD\_BIN\_50\_x\_KNOWLEDGE\_MED FIELD\_BIN\_50\_x\_KNOWLEDGE\_MED 0.02878289 1  
## FIELD\_BIN\_50\_x\_KNOWLEDGE\_AVG FIELD\_BIN\_50\_x\_KNOWLEDGE\_AVG 0.02878289 1  
## COLLECT\_BIN\_x\_KNOWLEDGE\_MED COLLECT\_BIN\_x\_KNOWLEDGE\_MED 4.15584416 1  
## COLLECT\_BIN\_x\_KNOWLEDGE\_AVG COLLECT\_BIN\_x\_KNOWLEDGE\_AVG 4.15584416 1  
## HANDLE\_BIN\_x\_KNOWLEDGE\_MED HANDLE\_BIN\_x\_KNOWLEDGE\_MED 0.27534965 1  
## HANDLE\_BIN\_x\_KNOWLEDGE\_AVG HANDLE\_BIN\_x\_KNOWLEDGE\_AVG 0.27534965 1  
## p\_value CramerV Effect\_Size Significant  
## CONTACT\_BIN\_x\_KNOWLEDGE\_MED 0.17625225 0.12860 Small FALSE  
## CONTACT\_BIN\_x\_KNOWLEDGE\_AVG 0.17625225 0.12860 Small FALSE  
## FIELD\_BIN\_MED\_x\_KNOWLEDGE\_MED 0.86528129 0.02868 Negligible FALSE  
## FIELD\_BIN\_MED\_x\_KNOWLEDGE\_AVG 0.86528129 0.02868 Negligible FALSE  
## FIELD\_BIN\_50\_x\_KNOWLEDGE\_MED 0.86528129 0.02868 Negligible FALSE  
## FIELD\_BIN\_50\_x\_KNOWLEDGE\_AVG 0.86528129 0.02868 Negligible FALSE  
## COLLECT\_BIN\_x\_KNOWLEDGE\_MED 0.04149109 0.18660 Small TRUE  
## COLLECT\_BIN\_x\_KNOWLEDGE\_AVG 0.04149109 0.18660 Small TRUE  
## HANDLE\_BIN\_x\_KNOWLEDGE\_MED 0.59976555 0.05913 Negligible FALSE  
## HANDLE\_BIN\_x\_KNOWLEDGE\_AVG 0.59976555 0.05913 Negligible FALSE  
##   
## $prac\_conf  
## Variable\_Pair Chi\_Square df  
## CONTACT\_BIN\_x\_CONFIDENCE\_MED CONTACT\_BIN\_x\_CONFIDENCE\_MED 1.803211047 1  
## CONTACT\_BIN\_x\_CONFIDENCE\_AVG CONTACT\_BIN\_x\_CONFIDENCE\_AVG 1.803211047 1  
## FIELD\_BIN\_MED\_x\_CONFIDENCE\_MED FIELD\_BIN\_MED\_x\_CONFIDENCE\_MED 0.179159318 1  
## FIELD\_BIN\_MED\_x\_CONFIDENCE\_AVG FIELD\_BIN\_MED\_x\_CONFIDENCE\_AVG 0.179159318 1  
## FIELD\_BIN\_50\_x\_CONFIDENCE\_MED FIELD\_BIN\_50\_x\_CONFIDENCE\_MED 0.179159318 1  
## FIELD\_BIN\_50\_x\_CONFIDENCE\_AVG FIELD\_BIN\_50\_x\_CONFIDENCE\_AVG 0.179159318 1  
## COLLECT\_BIN\_x\_CONFIDENCE\_MED COLLECT\_BIN\_x\_CONFIDENCE\_MED 0.615198033 1  
## COLLECT\_BIN\_x\_CONFIDENCE\_AVG COLLECT\_BIN\_x\_CONFIDENCE\_AVG 0.615198033 1  
## HANDLE\_BIN\_x\_CONFIDENCE\_MED HANDLE\_BIN\_x\_CONFIDENCE\_MED 0.009082714 1  
## HANDLE\_BIN\_x\_CONFIDENCE\_AVG HANDLE\_BIN\_x\_CONFIDENCE\_AVG 0.009082714 1  
## p\_value CramerV Effect\_Size Significant  
## CONTACT\_BIN\_x\_CONFIDENCE\_MED 0.1793248 0.12780 Small FALSE  
## CONTACT\_BIN\_x\_CONFIDENCE\_AVG 0.1793248 0.12780 Small FALSE  
## FIELD\_BIN\_MED\_x\_CONFIDENCE\_MED 0.6720967 0.05016 Negligible FALSE  
## FIELD\_BIN\_MED\_x\_CONFIDENCE\_AVG 0.6720967 0.05016 Negligible FALSE  
## FIELD\_BIN\_50\_x\_CONFIDENCE\_MED 0.6720967 0.05016 Negligible FALSE  
## FIELD\_BIN\_50\_x\_CONFIDENCE\_AVG 0.6720967 0.05016 Negligible FALSE  
## COLLECT\_BIN\_x\_CONFIDENCE\_MED 0.4328373 0.08070 Negligible FALSE  
## COLLECT\_BIN\_x\_CONFIDENCE\_AVG 0.4328373 0.08070 Negligible FALSE  
## HANDLE\_BIN\_x\_CONFIDENCE\_MED 0.9240739 0.02289 Negligible FALSE  
## HANDLE\_BIN\_x\_CONFIDENCE\_AVG 0.9240739 0.02289 Negligible FALSE  
##   
## $pracsco\_know  
## Variable\_Pair Chi\_Square df p\_value  
## PRACTICE\_AVG\_x\_KNOWLEDGE\_MED PRACTICE\_AVG\_x\_KNOWLEDGE\_MED 0 1 1  
## PRACTICE\_AVG\_x\_KNOWLEDGE\_AVG PRACTICE\_AVG\_x\_KNOWLEDGE\_AVG 0 1 1  
## PRACTICE\_MED\_x\_KNOWLEDGE\_MED PRACTICE\_MED\_x\_KNOWLEDGE\_MED 0 1 1  
## PRACTICE\_MED\_x\_KNOWLEDGE\_AVG PRACTICE\_MED\_x\_KNOWLEDGE\_AVG 0 1 1  
## CramerV Effect\_Size Significant  
## PRACTICE\_AVG\_x\_KNOWLEDGE\_MED 0.01529 Negligible FALSE  
## PRACTICE\_AVG\_x\_KNOWLEDGE\_AVG 0.01529 Negligible FALSE  
## PRACTICE\_MED\_x\_KNOWLEDGE\_MED 0.01529 Negligible FALSE  
## PRACTICE\_MED\_x\_KNOWLEDGE\_AVG 0.01529 Negligible FALSE  
##   
## $pracsco\_conf  
## Variable\_Pair Chi\_Square df  
## PRACTICE\_AVG\_x\_CONFIDENCE\_MED PRACTICE\_AVG\_x\_CONFIDENCE\_MED 5.353765e-31 1  
## PRACTICE\_AVG\_x\_CONFIDENCE\_AVG PRACTICE\_AVG\_x\_CONFIDENCE\_AVG 5.353765e-31 1  
## PRACTICE\_MED\_x\_CONFIDENCE\_MED PRACTICE\_MED\_x\_CONFIDENCE\_MED 5.353765e-31 1  
## PRACTICE\_MED\_x\_CONFIDENCE\_AVG PRACTICE\_MED\_x\_CONFIDENCE\_AVG 5.353765e-31 1  
## p\_value CramerV Effect\_Size Significant  
## PRACTICE\_AVG\_x\_CONFIDENCE\_MED 1 0.01316 Negligible FALSE  
## PRACTICE\_AVG\_x\_CONFIDENCE\_AVG 1 0.01316 Negligible FALSE  
## PRACTICE\_MED\_x\_CONFIDENCE\_MED 1 0.01316 Negligible FALSE  
## PRACTICE\_MED\_x\_CONFIDENCE\_AVG 1 0.01316 Negligible FALSE  
##   
## $ppe\_prac  
## Variable\_Pair Chi\_Square df p\_value  
## PPE\_BIN\_x\_CONTACT\_BIN PPE\_BIN\_x\_CONTACT\_BIN 0.01257872 1 0.910700580  
## PPE\_BIN\_x\_FIELD\_BIN\_MED PPE\_BIN\_x\_FIELD\_BIN\_MED 7.78443319 1 0.005269832  
## PPE\_BIN\_x\_FIELD\_BIN\_50 PPE\_BIN\_x\_FIELD\_BIN\_50 7.78443319 1 0.005269832  
## PPE\_BIN\_x\_COLLECT\_BIN PPE\_BIN\_x\_COLLECT\_BIN 0.38757038 1 0.533579284  
## PPE\_BIN\_x\_HANDLE\_BIN PPE\_BIN\_x\_HANDLE\_BIN 0.01257872 1 0.910700580  
## CramerV Effect\_Size Significant  
## PPE\_BIN\_x\_CONTACT\_BIN 0.03440 Negligible FALSE  
## PPE\_BIN\_x\_FIELD\_BIN\_MED 0.29620 Small TRUE  
## PPE\_BIN\_x\_FIELD\_BIN\_50 0.29620 Small TRUE  
## PPE\_BIN\_x\_COLLECT\_BIN 0.08447 Negligible FALSE  
## PPE\_BIN\_x\_HANDLE\_BIN 0.03440 Negligible FALSE  
##   
## $ppe\_pracsco  
## Variable\_Pair Chi\_Square df p\_value CramerV  
## PPE\_BIN\_x\_PRACTICE\_AVG PPE\_BIN\_x\_PRACTICE\_AVG 0.1796961 1 0.6716346 0.06619  
## PPE\_BIN\_x\_PRACTICE\_MED PPE\_BIN\_x\_PRACTICE\_MED 0.1796961 1 0.6716346 0.06619  
## Effect\_Size Significant  
## PPE\_BIN\_x\_PRACTICE\_AVG Negligible FALSE  
## PPE\_BIN\_x\_PRACTICE\_MED Negligible FALSE  
##   
## $sources\_know  
## Variable\_Pair  
## SOURCE\_TRUST\_BIN\_x\_PIGS\_BINK SOURCE\_TRUST\_BIN\_x\_PIGS\_BINK  
## SOURCE\_TRUST\_BIN\_x\_BRUCE\_BINK SOURCE\_TRUST\_BIN\_x\_BRUCE\_BINK  
## SOURCE\_TRUST\_BIN\_x\_CWD\_BINK SOURCE\_TRUST\_BIN\_x\_CWD\_BINK  
## SOURCE\_TRUST\_BIN\_x\_FLUAL\_BINK SOURCE\_TRUST\_BIN\_x\_FLUAL\_BINK  
## SOURCE\_TRUST\_BIN\_x\_FLU\_BINK SOURCE\_TRUST\_BIN\_x\_FLU\_BINK  
## SOURCE\_TRUST\_BIN\_x\_COVID\_BINK SOURCE\_TRUST\_BIN\_x\_COVID\_BINK  
## SOURCE\_TRUST\_BIN\_x\_COVIDSPILL\_BINK SOURCE\_TRUST\_BIN\_x\_COVIDSPILL\_BINK  
## SOURCE\_TRUST\_BIN\_x\_RABIESAL\_BINK SOURCE\_TRUST\_BIN\_x\_RABIESAL\_BINK  
## SOURCE\_TRUST\_BIN\_x\_RABIES\_BINK SOURCE\_TRUST\_BIN\_x\_RABIES\_BINK  
## SOURCE\_TRUST\_BIN\_x\_TURKEY\_BINK SOURCE\_TRUST\_BIN\_x\_TURKEY\_BINK  
## Chi\_Square df p\_value CramerV  
## SOURCE\_TRUST\_BIN\_x\_PIGS\_BINK 0.0000000 1 1.000000000 0.03203  
## SOURCE\_TRUST\_BIN\_x\_BRUCE\_BINK 1.0198135 1 0.312563247 0.10240  
## SOURCE\_TRUST\_BIN\_x\_CWD\_BINK 4.6910145 1 0.030320741 0.20460  
## SOURCE\_TRUST\_BIN\_x\_FLUAL\_BINK 3.4414946 1 0.063578154 0.17770  
## SOURCE\_TRUST\_BIN\_x\_FLU\_BINK 6.7724868 1 0.009257376 0.24740  
## SOURCE\_TRUST\_BIN\_x\_COVID\_BINK 2.2459893 1 0.133961208 0.14350  
## SOURCE\_TRUST\_BIN\_x\_COVIDSPILL\_BINK 3.8599393 1 0.049452116 0.18260  
## SOURCE\_TRUST\_BIN\_x\_RABIESAL\_BINK 0.4861111 1 0.485667196 0.07857  
## SOURCE\_TRUST\_BIN\_x\_RABIES\_BINK 0.4232804 1 0.515304699 0.08248  
## SOURCE\_TRUST\_BIN\_x\_TURKEY\_BINK 1.1582906 1 0.281820338 0.10750  
## Effect\_Size Significant  
## SOURCE\_TRUST\_BIN\_x\_PIGS\_BINK Negligible FALSE  
## SOURCE\_TRUST\_BIN\_x\_BRUCE\_BINK Small FALSE  
## SOURCE\_TRUST\_BIN\_x\_CWD\_BINK Small TRUE  
## SOURCE\_TRUST\_BIN\_x\_FLUAL\_BINK Small FALSE  
## SOURCE\_TRUST\_BIN\_x\_FLU\_BINK Small TRUE  
## SOURCE\_TRUST\_BIN\_x\_COVID\_BINK Small FALSE  
## SOURCE\_TRUST\_BIN\_x\_COVIDSPILL\_BINK Small TRUE  
## SOURCE\_TRUST\_BIN\_x\_RABIESAL\_BINK Negligible FALSE  
## SOURCE\_TRUST\_BIN\_x\_RABIES\_BINK Negligible FALSE  
## SOURCE\_TRUST\_BIN\_x\_TURKEY\_BINK Small FALSE

all\_results <- bind\_rows(lapply(names(results), function(name) {  
 df <- results[[name]]  
 if (is.data.frame(df)) {  
 df$Source <- name  
 return(df)  
 }  
}), .id = "Group")  
top\_results <- all\_results %>%  
 filter(Significant == TRUE) %>%  
 arrange(desc(CramerV)) %>%  
 select(Source, Variable\_Pair, Chi\_Square, df, p\_value, CramerV, Effect\_Size) %>%  
 head(50)   
knitr::kable(top\_results, format = "pandoc", caption = "Top 50 Most Significant Relationships")

Top 50 Most Significant Relationships

|  | Source | Variable\_Pair | Chi\_Square | df | p\_value | CramerV | Effect\_Size |
| --- | --- | --- | --- | --- | --- | --- | --- |
| KNOWLEDGE\_MED\_x\_CONFIDENCE\_MED | know\_conf | KNOWLEDGE\_MED\_x\_CONFIDENCE\_MED | 74.864309 | 1 | 0.0000000 | 0.7456 | Large |
| KNOWLEDGE\_MED\_x\_CONFIDENCE\_AVG | know\_conf | KNOWLEDGE\_MED\_x\_CONFIDENCE\_AVG | 74.864309 | 1 | 0.0000000 | 0.7456 | Large |
| KNOWLEDGE\_AVG\_x\_CONFIDENCE\_MED | know\_conf | KNOWLEDGE\_AVG\_x\_CONFIDENCE\_MED | 74.864309 | 1 | 0.0000000 | 0.7456 | Large |
| KNOWLEDGE\_AVG\_x\_CONFIDENCE\_AVG | know\_conf | KNOWLEDGE\_AVG\_x\_CONFIDENCE\_AVG | 74.864309 | 1 | 0.0000000 | 0.7456 | Large |
| MISINFO\_MED\_x\_CONFIDENCE\_MED | att\_conf | MISINFO\_MED\_x\_CONFIDENCE\_MED | 26.648189 | 1 | 0.0000002 | 0.4514 | Moderate |
| MISINFO\_MED\_x\_CONFIDENCE\_AVG | att\_conf | MISINFO\_MED\_x\_CONFIDENCE\_AVG | 26.648189 | 1 | 0.0000002 | 0.4514 | Moderate |
| MISINFO\_MED\_x\_KNOWLEDGE\_MED | att\_know | MISINFO\_MED\_x\_KNOWLEDGE\_MED | 19.814312 | 1 | 0.0000085 | 0.3913 | Moderate |
| MISINFO\_MED\_x\_KNOWLEDGE\_AVG | att\_know | MISINFO\_MED\_x\_KNOWLEDGE\_AVG | 19.814312 | 1 | 0.0000085 | 0.3913 | Moderate |
| MISINFO\_AVG\_x\_CONFIDENCE\_MED | att\_conf | MISINFO\_AVG\_x\_CONFIDENCE\_MED | 15.791327 | 1 | 0.0000707 | 0.3503 | Moderate |
| MISINFO\_AVG\_x\_CONFIDENCE\_AVG | att\_conf | MISINFO\_AVG\_x\_CONFIDENCE\_AVG | 15.791327 | 1 | 0.0000707 | 0.3503 | Moderate |
| STATE\_BIN\_x\_CONFIDENCE\_MED | demo\_conf | STATE\_BIN\_x\_CONFIDENCE\_MED | 4.312824 | 1 | 0.0378261 | 0.3287 | Moderate |
| STATE\_BIN\_x\_CONFIDENCE\_AVG | demo\_conf | STATE\_BIN\_x\_CONFIDENCE\_AVG | 4.312824 | 1 | 0.0378261 | 0.3287 | Moderate |
| MISINFO\_AVG\_x\_KNOWLEDGE\_MED | att\_know | MISINFO\_AVG\_x\_KNOWLEDGE\_MED | 11.620668 | 1 | 0.0006522 | 0.3025 | Moderate |
| MISINFO\_AVG\_x\_KNOWLEDGE\_AVG | att\_know | MISINFO\_AVG\_x\_KNOWLEDGE\_AVG | 11.620668 | 1 | 0.0006522 | 0.3025 | Moderate |
| PPE\_BIN\_x\_FIELD\_BIN\_MED | ppe\_prac | PPE\_BIN\_x\_FIELD\_BIN\_MED | 7.784433 | 1 | 0.0052698 | 0.2962 | Small |
| PPE\_BIN\_x\_FIELD\_BIN\_50 | ppe\_prac | PPE\_BIN\_x\_FIELD\_BIN\_50 | 7.784433 | 1 | 0.0052698 | 0.2962 | Small |
| BIOTIME\_BIN\_x\_CONFIDENCE\_MED | exp\_conf | BIOTIME\_BIN\_x\_CONFIDENCE\_MED | 10.021508 | 1 | 0.0015472 | 0.2826 | Small |
| BIOTIME\_BIN\_x\_CONFIDENCE\_AVG | exp\_conf | BIOTIME\_BIN\_x\_CONFIDENCE\_AVG | 10.021508 | 1 | 0.0015472 | 0.2826 | Small |
| LICENSE\_BIN\_x\_KNOWLEDGE\_MED | id\_know | LICENSE\_BIN\_x\_KNOWLEDGE\_MED | 9.098756 | 1 | 0.0025578 | 0.2709 | Small |
| LICENSE\_BIN\_x\_KNOWLEDGE\_AVG | id\_know | LICENSE\_BIN\_x\_KNOWLEDGE\_AVG | 9.098756 | 1 | 0.0025578 | 0.2709 | Small |
| LICENSE\_BIN\_x\_CONFIDENCE\_MED | id\_conf | LICENSE\_BIN\_x\_CONFIDENCE\_MED | 8.428631 | 1 | 0.0036936 | 0.2614 | Small |
| LICENSE\_BIN\_x\_CONFIDENCE\_AVG | id\_conf | LICENSE\_BIN\_x\_CONFIDENCE\_AVG | 8.428631 | 1 | 0.0036936 | 0.2614 | Small |
| DEGREE\_BIN\_x\_CONFIDENCE\_MED | edu\_conf | DEGREE\_BIN\_x\_CONFIDENCE\_MED | 7.871686 | 1 | 0.0050215 | 0.2546 | Small |
| DEGREE\_BIN\_x\_CONFIDENCE\_AVG | edu\_conf | DEGREE\_BIN\_x\_CONFIDENCE\_AVG | 7.871686 | 1 | 0.0050215 | 0.2546 | Small |
| DEMO\_EDU\_AVG\_x\_CONFIDENCE\_MED | edu\_conf | DEMO\_EDU\_AVG\_x\_CONFIDENCE\_MED | 7.871686 | 1 | 0.0050215 | 0.2546 | Small |
| DEMO\_EDU\_AVG\_x\_CONFIDENCE\_AVG | edu\_conf | DEMO\_EDU\_AVG\_x\_CONFIDENCE\_AVG | 7.871686 | 1 | 0.0050215 | 0.2546 | Small |
| BIOTIME\_BIN\_x\_KNOWLEDGE\_MED | exp\_know | BIOTIME\_BIN\_x\_KNOWLEDGE\_MED | 8.037677 | 1 | 0.0045814 | 0.2546 | Small |
| BIOTIME\_BIN\_x\_KNOWLEDGE\_AVG | exp\_know | BIOTIME\_BIN\_x\_KNOWLEDGE\_AVG | 8.037677 | 1 | 0.0045814 | 0.2546 | Small |
| DEMO\_EXP\_MED\_x\_KNOWLEDGE\_MED | exp\_know | DEMO\_EXP\_MED\_x\_KNOWLEDGE\_MED | 7.896012 | 1 | 0.0049544 | 0.2523 | Small |
| DEMO\_EXP\_MED\_x\_KNOWLEDGE\_AVG | exp\_know | DEMO\_EXP\_MED\_x\_KNOWLEDGE\_AVG | 7.896012 | 1 | 0.0049544 | 0.2523 | Small |
| DEMO\_EXP\_AVG\_x\_KNOWLEDGE\_MED | exp\_know | DEMO\_EXP\_AVG\_x\_KNOWLEDGE\_MED | 7.896012 | 1 | 0.0049544 | 0.2523 | Small |
| DEMO\_EXP\_AVG\_x\_KNOWLEDGE\_AVG | exp\_know | DEMO\_EXP\_AVG\_x\_KNOWLEDGE\_AVG | 7.896012 | 1 | 0.0049544 | 0.2523 | Small |
| COURSE\_BIN\_x\_CONFIDENCE\_MED | exp\_conf | COURSE\_BIN\_x\_CONFIDENCE\_MED | 7.868524 | 1 | 0.0050303 | 0.2517 | Small |
| COURSE\_BIN\_x\_CONFIDENCE\_AVG | exp\_conf | COURSE\_BIN\_x\_CONFIDENCE\_AVG | 7.868524 | 1 | 0.0050303 | 0.2517 | Small |
| SOURCE\_TRUST\_BIN\_x\_FLU\_BINK | sources\_know | SOURCE\_TRUST\_BIN\_x\_FLU\_BINK | 6.772487 | 1 | 0.0092574 | 0.2474 | Small |
| DEGREE\_BIN\_x\_KNOWLEDGE\_MED | edu\_know | DEGREE\_BIN\_x\_KNOWLEDGE\_MED | 7.169697 | 1 | 0.0074145 | 0.2437 | Small |
| DEGREE\_BIN\_x\_KNOWLEDGE\_AVG | edu\_know | DEGREE\_BIN\_x\_KNOWLEDGE\_AVG | 7.169697 | 1 | 0.0074145 | 0.2437 | Small |
| DEMO\_EDU\_AVG\_x\_KNOWLEDGE\_MED | edu\_know | DEMO\_EDU\_AVG\_x\_KNOWLEDGE\_MED | 7.169697 | 1 | 0.0074145 | 0.2437 | Small |
| DEMO\_EDU\_AVG\_x\_KNOWLEDGE\_AVG | edu\_know | DEMO\_EDU\_AVG\_x\_KNOWLEDGE\_AVG | 7.169697 | 1 | 0.0074145 | 0.2437 | Small |
| SELFTITLE\_BIN\_x\_KNOWLEDGE\_MED | id\_know | SELFTITLE\_BIN\_x\_KNOWLEDGE\_MED | 6.846065 | 1 | 0.0088837 | 0.2381 | Small |
| SELFTITLE\_BIN\_x\_KNOWLEDGE\_AVG | id\_know | SELFTITLE\_BIN\_x\_KNOWLEDGE\_AVG | 6.846065 | 1 | 0.0088837 | 0.2381 | Small |
| EDUCATION\_BIN\_x\_CONFIDENCE\_MED | edu\_conf | EDUCATION\_BIN\_x\_CONFIDENCE\_MED | 6.237300 | 1 | 0.0125087 | 0.2304 | Small |
| EDUCATION\_BIN\_x\_CONFIDENCE\_AVG | edu\_conf | EDUCATION\_BIN\_x\_CONFIDENCE\_AVG | 6.237300 | 1 | 0.0125087 | 0.2304 | Small |
| EDUCATION\_BIN\_x\_KNOWLEDGE\_MED | edu\_know | EDUCATION\_BIN\_x\_KNOWLEDGE\_MED | 5.921295 | 1 | 0.0149590 | 0.2248 | Small |
| EDUCATION\_BIN\_x\_KNOWLEDGE\_AVG | edu\_know | EDUCATION\_BIN\_x\_KNOWLEDGE\_AVG | 5.921295 | 1 | 0.0149590 | 0.2248 | Small |
| DIRECT\_AVG\_x\_CONFIDENCE\_MED | att\_conf | DIRECT\_AVG\_x\_CONFIDENCE\_MED | 6.022858 | 1 | 0.0141218 | 0.2218 | Small |
| DIRECT\_AVG\_x\_CONFIDENCE\_AVG | att\_conf | DIRECT\_AVG\_x\_CONFIDENCE\_AVG | 6.022858 | 1 | 0.0141218 | 0.2218 | Small |
| DIRECT\_MED\_x\_CONFIDENCE\_MED | att\_conf | DIRECT\_MED\_x\_CONFIDENCE\_MED | 6.022858 | 1 | 0.0141218 | 0.2218 | Small |
| DIRECT\_MED\_x\_CONFIDENCE\_AVG | att\_conf | DIRECT\_MED\_x\_CONFIDENCE\_AVG | 6.022858 | 1 | 0.0141218 | 0.2218 | Small |
| DEMO\_EXP\_MED\_x\_CONFIDENCE\_MED | exp\_conf | DEMO\_EXP\_MED\_x\_CONFIDENCE\_MED | 5.771265 | 1 | 0.0162903 | 0.2179 | Small |

#### 3.0.0.3 Export

require(openxlsx)  
wb <- createWorkbook()  
dir.create(oup, showWarnings = FALSE)  
  
for (name in names(results)) {  
 res <- results[[name]]  
 if (is.data.frame(res) && nrow(res) > 0) {  
 addWorksheet(wb, sheetName = paste0(name, "\_all"))  
 writeData(wb, sheet = paste0(name, "\_all"), res)  
 if ("Significant" %in% names(res)) {  
 sig\_res <- subset(res, Significant == TRUE)  
 addWorksheet(wb, sheetName = paste0(name, "\_sig"))  
 writeData(wb, sheet = paste0(name, "\_sig"), sig\_res)  
 }  
 }  
}  
saveWorkbook(wb, file = file.path(oup, "cramerchisq\_results.xlsx"), overwrite = TRUE)  
for (name in names(results)) {  
 res <- results[[name]]  
 if (is.data.frame(res) && nrow(res) > 0) {  
 if ("Significant" %in% names(res)) {  
 sig\_data <- subset(res, Significant == TRUE)  
 }  
 }  
}

# 4 Regression

require(tidyverse)  
require(MASS)  
require(broom)  
require(nnet)  
require(knitr)  
  
df$COURSE\_GROUP <- as.factor(df$COURSE\_GROUP)

#### 4.0.0.1 Linear Models

#### Pairs (Knowledge X Attitude) ------------  
# Define matched attitude/knowledge/confidence items  
attitude\_knowledge\_pairs <- list(  
 list(attitude = "CWDAL\_A", knowledge = "CWD\_BINK", confidence = "CWD\_BINC"),  
 list(attitude = "BATS\_A", knowledge = "FLUAL\_BINK", confidence = "FLUAL\_BINC"),  
 list(attitude = "PPEREQ\_A", knowledge = "BRUCE\_BINK", confidence = "BRUCE\_BINC"),  
 list(attitude = "EHD\_A", knowledge = "FLUAL\_BINK", confidence = "FLUAL\_BINC"),  
 list(attitude = "DARWIN\_A", knowledge = "COVIDSPILL\_BINK", confidence = "COVIDSPILL\_BINC"))  
  
run\_attitude\_models\_dual <- function(data, pairs) {  
 results <- list()  
 if (!"COURSEGROUP\_BIN" %in% names(data)) {  
 data <- data %>%  
 mutate(COURSEGROUP\_BIN = case\_when(  
 COURSE\_BIN == 0 ~ 0,  
 COURSETIME\_BIN == 1 ~ 1,  
 COURSETIME\_BIN == 0 ~ 2,  
 TRUE ~ NA\_real\_))  
 }  
 for (pair in pairs) {  
 att <- pair$attitude  
 acc <- pair$knowledge  
 conf <- pair$confidence  
 att\_num <- paste0(att, "\_NUM")  
 if (!all(c(att, acc, conf) %in% names(data))) {  
 warning(paste("Skipping due to missing variables:", att, acc, conf))  
 next  
 }  
 data[[att\_num]] <- as.numeric(data[[att]])  
 model\_acc <- lm(as.formula(paste(att\_num, "~", acc,  
 "+ KNOWLEDGE\_SCORE + INTEREST\_BIN + EDUCATION\_BIN + BIOTIME\_BIN + factor(COURSEGROUP\_BIN)")), data = data)  
 model\_conf <- lm(as.formula(paste(att\_num, "~", conf,  
 "+ KNOWLEDGE\_SCORE + INTEREST\_BIN + EDUCATION\_BIN + BIOTIME\_BIN + factor(COURSEGROUP\_BIN)")), data = data)  
  
 results[[att]] <- list(  
 accuracy\_model = summary(model\_acc),  
 confidence\_model = summary(model\_conf)  
 )  
 }  
 return(results)  
}  
pairslm\_result <- run\_attitude\_models\_dual(df, attitude\_knowledge\_pairs)  
pairslm\_result

## $CWDAL\_A  
## $CWDAL\_A$accuracy\_model  
##   
## Call:  
## lm(formula = as.formula(paste(att\_num, "~", acc, "+ KNOWLEDGE\_SCORE + INTEREST\_BIN + EDUCATION\_BIN + BIOTIME\_BIN + factor(COURSEGROUP\_BIN)")),   
## data = data)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -2.24467 -0.45536 0.03095 0.65754 1.30944   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 1.96533 0.36316 5.412 2.96e-07 \*\*\*  
## CWD\_BINK 0.28846 0.22506 1.282 0.20227   
## KNOWLEDGE\_SCORE 0.10353 0.04405 2.350 0.02028 \*   
## INTEREST\_BIN 0.26990 0.27423 0.984 0.32687   
## EDUCATION\_BIN 0.64920 0.19954 3.254 0.00146 \*\*   
## BIOTIME\_BIN 0.23776 0.18431 1.290 0.19937   
## factor(COURSEGROUP\_BIN)1 -0.03208 0.19524 -0.164 0.86974   
## factor(COURSEGROUP\_BIN)2 -0.20132 0.20900 -0.963 0.33724   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 0.858 on 128 degrees of freedom  
## (4 observations deleted due to missingness)  
## Multiple R-squared: 0.2518, Adjusted R-squared: 0.2109   
## F-statistic: 6.154 on 7 and 128 DF, p-value: 3.26e-06  
##   
##   
## $CWDAL\_A$confidence\_model  
##   
## Call:  
## lm(formula = as.formula(paste(att\_num, "~", conf, "+ KNOWLEDGE\_SCORE + INTEREST\_BIN + EDUCATION\_BIN + BIOTIME\_BIN + factor(COURSEGROUP\_BIN)")),   
## data = data)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -2.26711 -0.46613 0.02075 0.66394 1.39661   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 2.05654 0.37509 5.483 2.14e-07 \*\*\*  
## CWD\_BINC -0.12290 0.38085 -0.323 0.747455   
## KNOWLEDGE\_SCORE 0.12529 0.04132 3.032 0.002941 \*\*   
## INTEREST\_BIN 0.23850 0.27501 0.867 0.387418   
## EDUCATION\_BIN 0.68192 0.20017 3.407 0.000879 \*\*\*  
## BIOTIME\_BIN 0.23152 0.18605 1.244 0.215624   
## factor(COURSEGROUP\_BIN)1 -0.04974 0.19596 -0.254 0.800046   
## factor(COURSEGROUP\_BIN)2 -0.19423 0.21063 -0.922 0.358180   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 0.8631 on 128 degrees of freedom  
## (4 observations deleted due to missingness)  
## Multiple R-squared: 0.2428, Adjusted R-squared: 0.2014   
## F-statistic: 5.864 on 7 and 128 DF, p-value: 6.429e-06  
##   
##   
##   
## $BATS\_A  
## $BATS\_A$accuracy\_model  
##   
## Call:  
## lm(formula = as.formula(paste(att\_num, "~", acc, "+ KNOWLEDGE\_SCORE + INTEREST\_BIN + EDUCATION\_BIN + BIOTIME\_BIN + factor(COURSEGROUP\_BIN)")),   
## data = data)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -2.3309 -1.0871 0.3157 0.8173 1.9252   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 3.15503 0.46455 6.792 3.74e-10 \*\*\*  
## FLUAL\_BINK -0.10508 0.27975 -0.376 0.708   
## KNOWLEDGE\_SCORE 0.04941 0.05511 0.897 0.372   
## INTEREST\_BIN 0.16178 0.35117 0.461 0.646   
## EDUCATION\_BIN -0.32552 0.25302 -1.287 0.201   
## BIOTIME\_BIN -0.20674 0.23461 -0.881 0.380   
## factor(COURSEGROUP\_BIN)1 0.04715 0.24715 0.191 0.849   
## factor(COURSEGROUP\_BIN)2 0.06620 0.26711 0.248 0.805   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 1.089 on 128 degrees of freedom  
## (4 observations deleted due to missingness)  
## Multiple R-squared: 0.03056, Adjusted R-squared: -0.02246   
## F-statistic: 0.5764 on 7 and 128 DF, p-value: 0.7741  
##   
##   
## $BATS\_A$confidence\_model  
##   
## Call:  
## lm(formula = as.formula(paste(att\_num, "~", conf, "+ KNOWLEDGE\_SCORE + INTEREST\_BIN + EDUCATION\_BIN + BIOTIME\_BIN + factor(COURSEGROUP\_BIN)")),   
## data = data)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -2.3335 -1.0873 0.3087 0.8026 1.9219   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 3.10897 0.48267 6.441 2.19e-09 \*\*\*  
## FLUAL\_BINC 0.02899 0.30673 0.095 0.925   
## KNOWLEDGE\_SCORE 0.04243 0.05378 0.789 0.432   
## INTEREST\_BIN 0.17572 0.35466 0.495 0.621   
## EDUCATION\_BIN -0.33314 0.25279 -1.318 0.190   
## BIOTIME\_BIN -0.21294 0.23482 -0.907 0.366   
## factor(COURSEGROUP\_BIN)1 0.04943 0.24904 0.198 0.843   
## factor(COURSEGROUP\_BIN)2 0.07840 0.26514 0.296 0.768   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 1.089 on 128 degrees of freedom  
## (4 observations deleted due to missingness)  
## Multiple R-squared: 0.02956, Adjusted R-squared: -0.02351   
## F-statistic: 0.5569 on 7 and 128 DF, p-value: 0.7896  
##   
##   
##   
## $PPEREQ\_A  
## $PPEREQ\_A$accuracy\_model  
##   
## Call:  
## lm(formula = as.formula(paste(att\_num, "~", acc, "+ KNOWLEDGE\_SCORE + INTEREST\_BIN + EDUCATION\_BIN + BIOTIME\_BIN + factor(COURSEGROUP\_BIN)")),   
## data = data)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -2.7388 -0.5834 0.2842 0.4304 1.8008   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 3.18731 0.43216 7.375 1.82e-11 \*\*\*  
## BRUCE\_BINK -0.11430 0.22605 -0.506 0.614   
## KNOWLEDGE\_SCORE 0.02634 0.05564 0.473 0.637   
## INTEREST\_BIN 0.39872 0.31996 1.246 0.215   
## EDUCATION\_BIN -0.13921 0.23237 -0.599 0.550   
## BIOTIME\_BIN 0.05473 0.21512 0.254 0.800   
## factor(COURSEGROUP\_BIN)1 0.10904 0.22705 0.480 0.632   
## factor(COURSEGROUP\_BIN)2 0.31083 0.24350 1.277 0.204   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 1 on 128 degrees of freedom  
## (4 observations deleted due to missingness)  
## Multiple R-squared: 0.03358, Adjusted R-squared: -0.01927   
## F-statistic: 0.6354 on 7 and 128 DF, p-value: 0.7259  
##   
##   
## $PPEREQ\_A$confidence\_model  
##   
## Call:  
## lm(formula = as.formula(paste(att\_num, "~", conf, "+ KNOWLEDGE\_SCORE + INTEREST\_BIN + EDUCATION\_BIN + BIOTIME\_BIN + factor(COURSEGROUP\_BIN)")),   
## data = data)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -2.8449 -0.6108 0.2716 0.4298 1.7333   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 3.400378 0.495157 6.867 2.54e-10 \*\*\*  
## BRUCE\_BINC -0.149973 0.244893 -0.612 0.541   
## KNOWLEDGE\_SCORE -0.008403 0.054945 -0.153 0.879   
## INTEREST\_BIN 0.386809 0.318412 1.215 0.227   
## EDUCATION\_BIN -0.109172 0.233006 -0.469 0.640   
## BIOTIME\_BIN 0.042738 0.214529 0.199 0.842   
## factor(COURSEGROUP\_BIN)1 0.108081 0.226958 0.476 0.635   
## factor(COURSEGROUP\_BIN)2 0.304569 0.243861 1.249 0.214   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 0.9995 on 128 degrees of freedom  
## (4 observations deleted due to missingness)  
## Multiple R-squared: 0.03448, Adjusted R-squared: -0.01832   
## F-statistic: 0.653 on 7 and 128 DF, p-value: 0.7113  
##   
##   
##   
## $EHD\_A  
## $EHD\_A$accuracy\_model  
##   
## Call:  
## lm(formula = as.formula(paste(att\_num, "~", acc, "+ KNOWLEDGE\_SCORE + INTEREST\_BIN + EDUCATION\_BIN + BIOTIME\_BIN + factor(COURSEGROUP\_BIN)")),   
## data = data)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -2.8249 -0.5800 0.1105 0.5451 2.0366   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 2.32884 0.35852 6.496 1.67e-09 \*\*\*  
## FLUAL\_BINK 0.42866 0.21590 1.985 0.04923 \*   
## KNOWLEDGE\_SCORE 0.10821 0.04253 2.544 0.01214 \*   
## INTEREST\_BIN -0.17851 0.27102 -0.659 0.51131   
## EDUCATION\_BIN 0.27204 0.19527 1.393 0.16599   
## BIOTIME\_BIN 0.53127 0.18106 2.934 0.00397 \*\*   
## factor(COURSEGROUP\_BIN)1 0.30280 0.19074 1.588 0.11486   
## factor(COURSEGROUP\_BIN)2 0.25418 0.20615 1.233 0.21984   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 0.8401 on 128 degrees of freedom  
## (4 observations deleted due to missingness)  
## Multiple R-squared: 0.3143, Adjusted R-squared: 0.2768   
## F-statistic: 8.382 on 7 and 128 DF, p-value: 2.066e-08  
##   
##   
## $EHD\_A$confidence\_model  
##   
## Call:  
## lm(formula = as.formula(paste(att\_num, "~", conf, "+ KNOWLEDGE\_SCORE + INTEREST\_BIN + EDUCATION\_BIN + BIOTIME\_BIN + factor(COURSEGROUP\_BIN)")),   
## data = data)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -2.8357 -0.5441 0.1120 0.5428 2.0350   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 2.65811 0.37392 7.109 7.32e-11 \*\*\*  
## FLUAL\_BINC -0.39843 0.23762 -1.677 0.09603 .   
## KNOWLEDGE\_SCORE 0.11808 0.04166 2.834 0.00534 \*\*   
## INTEREST\_BIN -0.16804 0.27475 -0.612 0.54189   
## EDUCATION\_BIN 0.28289 0.19584 1.445 0.15103   
## BIOTIME\_BIN 0.53534 0.18191 2.943 0.00386 \*\*   
## factor(COURSEGROUP\_BIN)1 0.26646 0.19293 1.381 0.16964   
## factor(COURSEGROUP\_BIN)2 0.21087 0.20540 1.027 0.30653   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 0.8438 on 128 degrees of freedom  
## (4 observations deleted due to missingness)  
## Multiple R-squared: 0.3084, Adjusted R-squared: 0.2706   
## F-statistic: 8.154 on 7 and 128 DF, p-value: 3.425e-08  
##   
##   
##   
## $DARWIN\_A  
## $DARWIN\_A$accuracy\_model  
##   
## Call:  
## lm(formula = as.formula(paste(att\_num, "~", acc, "+ KNOWLEDGE\_SCORE + INTEREST\_BIN + EDUCATION\_BIN + BIOTIME\_BIN + factor(COURSEGROUP\_BIN)")),   
## data = data)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -2.02193 -0.37959 -0.01314 0.58493 1.45812   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 3.02960 0.31255 9.693 <2e-16 \*\*\*  
## COVIDSPILL\_BINK 0.21202 0.15425 1.375 0.1717   
## KNOWLEDGE\_SCORE 0.01777 0.03989 0.445 0.6568   
## INTEREST\_BIN 0.40568 0.23491 1.727 0.0866 .   
## EDUCATION\_BIN 0.43573 0.17046 2.556 0.0117 \*   
## BIOTIME\_BIN 0.02656 0.15740 0.169 0.8663   
## factor(COURSEGROUP\_BIN)1 0.33757 0.16656 2.027 0.0448 \*   
## factor(COURSEGROUP\_BIN)2 0.14779 0.17855 0.828 0.4094   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 0.7336 on 128 degrees of freedom  
## (4 observations deleted due to missingness)  
## Multiple R-squared: 0.1489, Adjusted R-squared: 0.1024   
## F-statistic: 3.2 on 7 and 128 DF, p-value: 0.003716  
##   
##   
## $DARWIN\_A$confidence\_model  
##   
## Call:  
## lm(formula = as.formula(paste(att\_num, "~", conf, "+ KNOWLEDGE\_SCORE + INTEREST\_BIN + EDUCATION\_BIN + BIOTIME\_BIN + factor(COURSEGROUP\_BIN)")),   
## data = data)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -1.94761 -0.39392 0.06305 0.57580 1.24956   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 3.26161 0.33114 9.850 <2e-16 \*\*\*  
## COVIDSPILL\_BINC -0.32280 0.13901 -2.322 0.0218 \*   
## KNOWLEDGE\_SCORE 0.01620 0.03572 0.454 0.6509   
## INTEREST\_BIN 0.39161 0.23072 1.697 0.0921 .   
## EDUCATION\_BIN 0.46880 0.16912 2.772 0.0064 \*\*   
## BIOTIME\_BIN 0.03496 0.15532 0.225 0.8223   
## factor(COURSEGROUP\_BIN)1 0.32688 0.16438 1.989 0.0489 \*   
## factor(COURSEGROUP\_BIN)2 0.10924 0.17714 0.617 0.5386   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 0.7239 on 128 degrees of freedom  
## (4 observations deleted due to missingness)  
## Multiple R-squared: 0.1713, Adjusted R-squared: 0.126   
## F-statistic: 3.779 on 7 and 128 DF, p-value: 0.0009274

#--------------------------------------------------------------------------------  
df$KNOWLEDGE\_SCORE\_NORM <- scale(df$KNOWLEDGE\_SCORE)  
df$CONFIDENCE\_SCORE\_NORM <- scale(df$CONFIDENCE\_SCORE)  
  
# Knowledge Model  
know\_lm <- lm(KNOWLEDGE\_SCORE\_NORM ~ COURSE\_GROUP + AFFILIATE\_GROUP +  
 PRACTICE\_EXPOSURE\_SCORE + ATT\_CONCERN\_SCORE +  
 ATT\_MISINFO\_SCORE + INTEREST\_BIN, data = df)  
summary(know\_lm)

##   
## Call:  
## lm(formula = KNOWLEDGE\_SCORE\_NORM ~ COURSE\_GROUP + AFFILIATE\_GROUP +   
## PRACTICE\_EXPOSURE\_SCORE + ATT\_CONCERN\_SCORE + ATT\_MISINFO\_SCORE +   
## INTEREST\_BIN, data = df)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -1.96600 -0.52727 0.05397 0.61910 2.12167   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) -3.7036116 0.6272712 -5.904 3.08e-08 \*\*\*  
## COURSE\_GROUPOlder 0.2413278 0.2084820 1.158 0.24924   
## COURSE\_GROUPRecent -0.0095334 0.1880577 -0.051 0.95965   
## AFFILIATE\_GROUPGovernment 0.5675256 0.1849868 3.068 0.00264 \*\*   
## AFFILIATE\_GROUPNonprofit 0.1856974 0.3058890 0.607 0.54489   
## AFFILIATE\_GROUPOther -0.1822244 0.5344790 -0.341 0.73372   
## AFFILIATE\_GROUPPrivate 0.1833619 0.2412400 0.760 0.44863   
## PRACTICE\_EXPOSURE\_SCORE 0.0007085 0.0556413 0.013 0.98986   
## ATT\_CONCERN\_SCORE 0.1681295 0.1072844 1.567 0.11959   
## ATT\_MISINFO\_SCORE 0.6526288 0.1132621 5.762 6.02e-08 \*\*\*  
## INTEREST\_BIN 0.2704176 0.2693573 1.004 0.31733   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 0.8471 on 126 degrees of freedom  
## (3 observations deleted due to missingness)  
## Multiple R-squared: 0.3387, Adjusted R-squared: 0.2862   
## F-statistic: 6.454 on 10 and 126 DF, p-value: 5.532e-08

# Confidence Model  
conf\_lm <- lm(CONFIDENCE\_SCORE\_NORM ~ COURSE\_GROUP + AFFILIATE\_GROUP +  
 PRACTICE\_EXPOSURE\_SCORE + ATT\_CONCERN\_SCORE +  
 ATT\_MISINFO\_SCORE + INTEREST\_BIN, data = df)  
summary(conf\_lm)

##   
## Call:  
## lm(formula = CONFIDENCE\_SCORE\_NORM ~ COURSE\_GROUP + AFFILIATE\_GROUP +   
## PRACTICE\_EXPOSURE\_SCORE + ATT\_CONCERN\_SCORE + ATT\_MISINFO\_SCORE +   
## INTEREST\_BIN, data = df)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -1.94690 -0.53238 -0.07285 0.54931 2.60169   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 4.07795 0.61971 6.580 1.14e-09 \*\*\*  
## COURSE\_GROUPOlder -0.31589 0.20597 -1.534 0.12761   
## COURSE\_GROUPRecent -0.12896 0.18579 -0.694 0.48889   
## AFFILIATE\_GROUPGovernment -0.56847 0.18276 -3.110 0.00231 \*\*   
## AFFILIATE\_GROUPNonprofit -0.15507 0.30220 -0.513 0.60875   
## AFFILIATE\_GROUPOther -1.07029 0.52804 -2.027 0.04478 \*   
## AFFILIATE\_GROUPPrivate -0.33822 0.23833 -1.419 0.15834   
## PRACTICE\_EXPOSURE\_SCORE 0.01743 0.05497 0.317 0.75178   
## ATT\_CONCERN\_SCORE -0.22381 0.10599 -2.112 0.03670 \*   
## ATT\_MISINFO\_SCORE -0.68631 0.11190 -6.133 1.03e-08 \*\*\*  
## INTEREST\_BIN -0.25591 0.26611 -0.962 0.33807   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 0.8369 on 126 degrees of freedom  
## (3 observations deleted due to missingness)  
## Multiple R-squared: 0.3603, Adjusted R-squared: 0.3095   
## F-statistic: 7.096 on 10 and 126 DF, p-value: 8.671e-09

#### 4.0.0.2 Binomial

# Factor conversions -----------------------  
df$INTEREST\_BIN <- as.factor(df$INTEREST\_BIN)  
df$PPE\_BIN <- as.factor(df$PPE\_BIN)  
df$ACCESS\_BIN <- as.factor(df$ACCESS\_BIN)  
  
# Interest in Education ---------------------  
interest\_glm <- glm(INTEREST\_BIN ~ COURSE\_GROUP + AFFILIATE\_GROUP +  
 DEMO\_EDU\_SCORE + DEMO\_EXP\_SCORE +  
 KNOWLEDGE\_SCORE + PRACTICE\_EXPOSURE\_SCORE,  
 data = df, family = binomial)  
summary(interest\_glm)

##   
## Call:  
## glm(formula = INTEREST\_BIN ~ COURSE\_GROUP + AFFILIATE\_GROUP +   
## DEMO\_EDU\_SCORE + DEMO\_EXP\_SCORE + KNOWLEDGE\_SCORE + PRACTICE\_EXPOSURE\_SCORE,   
## family = binomial, data = df)  
##   
## Coefficients:  
## Estimate Std. Error z value Pr(>|z|)  
## (Intercept) 0.1837 1.2801 0.143 0.886  
## COURSE\_GROUPOlder 1.2271 1.3232 0.927 0.354  
## COURSE\_GROUPRecent 0.5049 0.8857 0.570 0.569  
## AFFILIATE\_GROUPGovernment -1.2540 0.9001 -1.393 0.164  
## AFFILIATE\_GROUPNonprofit 16.0200 1881.3701 0.009 0.993  
## AFFILIATE\_GROUPOther -1.5345 1.7429 -0.880 0.379  
## AFFILIATE\_GROUPPrivate -0.7150 1.1507 -0.621 0.534  
## DEMO\_EDU\_SCORE -0.2283 0.4662 -0.490 0.624  
## DEMO\_EXP\_SCORE 0.7399 0.5237 1.413 0.158  
## KNOWLEDGE\_SCORE 0.2393 0.1652 1.449 0.147  
## PRACTICE\_EXPOSURE\_SCORE 0.3839 0.2583 1.486 0.137  
##   
## (Dispersion parameter for binomial family taken to be 1)  
##   
## Null deviance: 81.359 on 136 degrees of freedom  
## Residual deviance: 66.602 on 126 degrees of freedom  
## (3 observations deleted due to missingness)  
## AIC: 88.602  
##   
## Number of Fisher Scoring iterations: 17

exp(coef(interest\_glm))

## (Intercept) COURSE\_GROUPOlder COURSE\_GROUPRecent   
## 1.201626e+00 3.411258e+00 1.656741e+00   
## AFFILIATE\_GROUPGovernment AFFILIATE\_GROUPNonprofit AFFILIATE\_GROUPOther   
## 2.853632e-01 9.065510e+06 2.155635e-01   
## AFFILIATE\_GROUPPrivate DEMO\_EDU\_SCORE DEMO\_EXP\_SCORE   
## 4.891690e-01 7.958711e-01 2.095623e+00   
## KNOWLEDGE\_SCORE PRACTICE\_EXPOSURE\_SCORE   
## 1.270336e+00 1.467953e+00

# PPE Use --------------------------  
ppe\_glm <- glm(PPE\_BIN ~ COURSE\_GROUP + AFFILIATE\_GROUP +  
 DEMO\_EDU\_SCORE + DEMO\_EXP\_SCORE +  
 KNOWLEDGE\_SCORE + PRACTICE\_EXPOSURE\_SCORE,  
 data = df, family = binomial)  
summary(ppe\_glm)

##   
## Call:  
## glm(formula = PPE\_BIN ~ COURSE\_GROUP + AFFILIATE\_GROUP + DEMO\_EDU\_SCORE +   
## DEMO\_EXP\_SCORE + KNOWLEDGE\_SCORE + PRACTICE\_EXPOSURE\_SCORE,   
## family = binomial, data = df)  
##   
## Coefficients:  
## Estimate Std. Error z value Pr(>|z|)   
## (Intercept) -0.6784 1.4113 -0.481 0.6307   
## COURSE\_GROUPOlder 2.1394 1.2675 1.688 0.0915 .  
## COURSE\_GROUPRecent 0.6543 0.7009 0.933 0.3506   
## AFFILIATE\_GROUPGovernment 0.8673 0.6335 1.369 0.1710   
## AFFILIATE\_GROUPNonprofit -1.1127 0.9910 -1.123 0.2615   
## AFFILIATE\_GROUPOther -1.6763 1.7263 -0.971 0.3315   
## AFFILIATE\_GROUPPrivate 0.2779 0.8877 0.313 0.7543   
## DEMO\_EDU\_SCORE -0.3823 0.4502 -0.849 0.3958   
## DEMO\_EXP\_SCORE -0.1546 0.3848 -0.402 0.6878   
## KNOWLEDGE\_SCORE 0.2424 0.1583 1.531 0.1257   
## PRACTICE\_EXPOSURE\_SCORE 0.2095 0.2127 0.985 0.3246   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## (Dispersion parameter for binomial family taken to be 1)  
##   
## Null deviance: 107.798 on 104 degrees of freedom  
## Residual deviance: 89.505 on 94 degrees of freedom  
## (35 observations deleted due to missingness)  
## AIC: 111.5  
##   
## Number of Fisher Scoring iterations: 6

exp(coef(ppe\_glm))

## (Intercept) COURSE\_GROUPOlder COURSE\_GROUPRecent   
## 0.5074136 8.4939318 1.9237773   
## AFFILIATE\_GROUPGovernment AFFILIATE\_GROUPNonprofit AFFILIATE\_GROUPOther   
## 2.3803833 0.3286800 0.1870561   
## AFFILIATE\_GROUPPrivate DEMO\_EDU\_SCORE DEMO\_EXP\_SCORE   
## 1.3203104 0.6823055 0.8567515   
## KNOWLEDGE\_SCORE PRACTICE\_EXPOSURE\_SCORE   
## 1.2743279 1.2330472

# Information Access  
access\_glm <- glm(ACCESS\_BIN ~ DEMO\_EDU\_SCORE + DEMO\_EXP\_SCORE +  
 KNOWLEDGE\_SCORE + PRACTICE\_EXPOSURE\_SCORE,  
 data = df, family = binomial)  
summary(access\_glm)

##   
## Call:  
## glm(formula = ACCESS\_BIN ~ DEMO\_EDU\_SCORE + DEMO\_EXP\_SCORE +   
## KNOWLEDGE\_SCORE + PRACTICE\_EXPOSURE\_SCORE, family = binomial,   
## data = df)  
##   
## Coefficients:  
## Estimate Std. Error z value Pr(>|z|)   
## (Intercept) -0.57709 0.76638 -0.753 0.4515   
## DEMO\_EDU\_SCORE 0.54558 0.31177 1.750 0.0801 .  
## DEMO\_EXP\_SCORE -0.18648 0.26100 -0.715 0.4749   
## KNOWLEDGE\_SCORE -0.15985 0.09792 -1.632 0.1026   
## PRACTICE\_EXPOSURE\_SCORE 0.07863 0.13965 0.563 0.5734   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## (Dispersion parameter for binomial family taken to be 1)  
##   
## Null deviance: 163.66 on 136 degrees of freedom  
## Residual deviance: 157.63 on 132 degrees of freedom  
## (3 observations deleted due to missingness)  
## AIC: 167.63  
##   
## Number of Fisher Scoring iterations: 4

exp(coef(access\_glm))

## (Intercept) DEMO\_EDU\_SCORE DEMO\_EXP\_SCORE   
## 0.5615323 1.7256158 0.8298728   
## KNOWLEDGE\_SCORE PRACTICE\_EXPOSURE\_SCORE   
## 0.8522742 1.0818008

#### 4.0.0.3 Multinomial

# Predicting Course Group -------------------------------------  
df$COURSE\_GROUP <- as.factor(df$COURSE\_GROUP)  
df$AFFILIATE\_GROUP <- as.factor(df$AFFILIATE\_GROUP)  
course\_mnom <- multinom(COURSE\_GROUP ~ CONFIDENCE\_SCORE + AFFILIATE\_GROUP +  
 DEMO\_EDU\_SCORE + DEMO\_EXP\_SCORE +  
 KNOWLEDGE\_SCORE + PRACTICE\_EXPOSURE\_SCORE,   
 data = df)

## # weights: 33 (20 variable)  
## initial value 153.805720   
## iter 10 value 112.936523  
## iter 20 value 107.835900  
## iter 30 value 107.586623  
## iter 40 value 107.582048  
## final value 107.582037   
## converged

summary(course\_mnom)

## Call:  
## multinom(formula = COURSE\_GROUP ~ CONFIDENCE\_SCORE + AFFILIATE\_GROUP +   
## DEMO\_EDU\_SCORE + DEMO\_EXP\_SCORE + KNOWLEDGE\_SCORE + PRACTICE\_EXPOSURE\_SCORE,   
## data = df)  
##   
## Coefficients:  
## (Intercept) CONFIDENCE\_SCORE AFFILIATE\_GROUPGovernment  
## Older -20.5603328 -0.8447137 1.9626680  
## Recent 0.9131581 -0.3930728 -0.2382664  
## AFFILIATE\_GROUPNonprofit AFFILIATE\_GROUPOther AFFILIATE\_GROUPPrivate  
## Older 1.64617224 23.4471860 2.3435416  
## Recent 0.05183294 0.4478703 -0.0921951  
## DEMO\_EDU\_SCORE DEMO\_EXP\_SCORE KNOWLEDGE\_SCORE PRACTICE\_EXPOSURE\_SCORE  
## Older 10.2567140 0.6652875 -0.3128826 -0.1696962  
## Recent -0.1586421 -0.2892881 -0.2197474 0.4624198  
##   
## Std. Errors:  
## (Intercept) CONFIDENCE\_SCORE AFFILIATE\_GROUPGovernment  
## Older 1.252596 0.3793643 1.113937  
## Recent 2.171706 0.2762833 0.551898  
## AFFILIATE\_GROUPNonprofit AFFILIATE\_GROUPOther AFFILIATE\_GROUPPrivate  
## Older 1.4079162 1.093768 1.2017137  
## Recent 0.9518048 1.638256 0.7597205  
## DEMO\_EDU\_SCORE DEMO\_EXP\_SCORE KNOWLEDGE\_SCORE PRACTICE\_EXPOSURE\_SCORE  
## Older 0.9095247 0.3200939 0.2670845 0.1998289  
## Recent 0.3163493 0.3433510 0.2332600 0.1873184  
##   
## Residual Deviance: 215.1641   
## AIC: 255.1641

exp(coef(course\_mnom))

## (Intercept) CONFIDENCE\_SCORE AFFILIATE\_GROUPGovernment  
## Older 1.176958e-09 0.4296804 7.1182933  
## Recent 2.492181e+00 0.6749796 0.7879928  
## AFFILIATE\_GROUPNonprofit AFFILIATE\_GROUPOther AFFILIATE\_GROUPPrivate  
## Older 5.187087 1.523995e+10 10.4180678  
## Recent 1.053200 1.564976e+00 0.9119272  
## DEMO\_EDU\_SCORE DEMO\_EXP\_SCORE KNOWLEDGE\_SCORE PRACTICE\_EXPOSURE\_SCORE  
## Older 2.847307e+04 1.9450497 0.7313358 0.8439211  
## Recent 8.533017e-01 0.7487964 0.8027215 1.5879117

z\_course <- summary(course\_mnom)$coefficients / summary(course\_mnom)$standard.errors  
course\_p <- 2 \* (1 - pnorm(abs(z\_course)))  
  
# Predicting Affiliate Group -----------------------  
affiliate\_mnom <- multinom(AFFILIATE\_GROUP ~ CONFIDENCE\_SCORE + COURSE\_GROUP +  
 DEMO\_EDU\_SCORE + DEMO\_EXP\_SCORE +  
 KNOWLEDGE\_SCORE + PRACTICE\_EXPOSURE\_SCORE,   
 data = df)

## # weights: 45 (32 variable)  
## initial value 225.321308   
## iter 10 value 170.962996  
## iter 20 value 156.932322  
## iter 30 value 153.224184  
## iter 40 value 152.098527  
## iter 50 value 151.871011  
## iter 60 value 151.672384  
## final value 151.670062   
## converged

summary(affiliate\_mnom)

## Call:  
## multinom(formula = AFFILIATE\_GROUP ~ CONFIDENCE\_SCORE + COURSE\_GROUP +   
## DEMO\_EDU\_SCORE + DEMO\_EXP\_SCORE + KNOWLEDGE\_SCORE + PRACTICE\_EXPOSURE\_SCORE,   
## data = df)  
##   
## Coefficients:  
## (Intercept) CONFIDENCE\_SCORE COURSE\_GROUPOlder COURSE\_GROUPRecent  
## Government -0.8169901 -0.06445607 1.887525 -0.28951862  
## Nonprofit 0.3753026 -0.03813417 1.923765 -0.08189059  
## Other -17.5199268 -41.72968993 240.261291 96.14899248  
## Private 2.6164846 -0.44455293 2.275006 -0.27238112  
## DEMO\_EDU\_SCORE DEMO\_EXP\_SCORE KNOWLEDGE\_SCORE  
## Government -0.3131435 0.2066441 0.2136000  
## Nonprofit 0.2294712 -0.2359373 -0.1221682  
## Other -112.1266755 -67.5715999 0.0703877  
## Private -0.5336367 0.5708073 -0.3387336  
## PRACTICE\_EXPOSURE\_SCORE  
## Government 0.10278262  
## Nonprofit -0.52750561  
## Other 8.77278080  
## Private 0.07206889  
##   
## Std. Errors:  
## (Intercept) CONFIDENCE\_SCORE COURSE\_GROUPOlder COURSE\_GROUPRecent  
## Government 2.364240 0.2747351 1.095041 0.5480952  
## Nonprofit 3.414939 0.3938818 1.390588 0.9663244  
## Other 26.871885 121.2212186 43.576447 51.2245640  
## Private 2.698080 0.3300587 1.174614 0.7469031  
## DEMO\_EDU\_SCORE DEMO\_EXP\_SCORE KNOWLEDGE\_SCORE  
## Government 0.3270613 3.053209e-01 0.2531819  
## Nonprofit 0.5527539 5.175753e-01 0.3651679  
## Other 87.1528950 1.043943e-10 0.9665074  
## Private 0.4324151 4.010463e-01 0.2997718  
## PRACTICE\_EXPOSURE\_SCORE  
## Government 0.1686377  
## Nonprofit 0.2814644  
## Other 13.6669284  
## Private 0.2180548  
##   
## Residual Deviance: 303.3401   
## AIC: 367.3401

exp(coef(affiliate\_mnom))

## (Intercept) CONFIDENCE\_SCORE COURSE\_GROUPOlder COURSE\_GROUPRecent  
## Government 4.417593e-01 9.375773e-01 6.603008e+00 7.486239e-01  
## Nonprofit 1.455432e+00 9.625838e-01 6.846687e+00 9.213728e-01  
## Other 2.461458e-08 7.534006e-19 2.208781e+104 5.714482e+41  
## Private 1.368752e+01 6.411108e-01 9.727978e+00 7.615640e-01  
## DEMO\_EDU\_SCORE DEMO\_EXP\_SCORE KNOWLEDGE\_SCORE  
## Government 7.311450e-01 1.229545e+00 1.2381273  
## Nonprofit 1.257935e+00 7.898302e-01 0.8849995  
## Other 2.013741e-49 4.508448e-30 1.0729241  
## Private 5.864683e-01 1.769695e+00 0.7126723  
## PRACTICE\_EXPOSURE\_SCORE  
## Government 1.108250  
## Nonprofit 0.590075  
## Other 6456.100678  
## Private 1.074729

z\_affil <- summary(affiliate\_mnom)$coefficients / summary(affiliate\_mnom)$standard.errors  
affil\_p <- 2 \* (1 - pnorm(abs(z\_affil)))

#### 4.0.0.4 Ordinal

likert\_items <- c("POPRED\_A", "POPPLAN\_A", "SURVEY\_A", "VACCINE\_A", "PREVAL\_A", "DIVERSE\_A",   
 "CONSEQ\_A", "CLIMATE\_A", "EDREQ\_A", "INFO\_A", "HANDSON\_A", "CWDAL\_A", "BATS\_A",  
 "PPEREQ\_A", "EHD\_A", "DARWIN\_A")  
results\_list <- list()  
for (item in likert\_items) {  
 df[[item]] <- factor(df[[item]], ordered = TRUE)  
 model <- polr(as.formula(paste(item, "~ KNOWLEDGE\_SCORE + CONFIDENCE\_SCORE + DEMO\_EDU\_SCORE + DEMO\_EXP\_SCORE +  
 GENDER\_BIN + AGE\_BIN")),  
 data = df, Hess = TRUE)  
 tidy\_out <- tidy(model) %>%  
 filter(str\_detect(term, "KNOWLEDGE\_SCORE|CONFIDENCE\_SCORE|DEMO\_|GENDER\_BIN|AGE\_BIN")) %>%  
 mutate(  
 p.value = 2 \* pnorm(abs(statistic), lower.tail = FALSE),  
 attitude\_item = item  
 )  
 results\_list[[item]] <- tidy\_out  
}  
results\_df <- bind\_rows(results\_list) %>%  
 mutate(  
 significant = ifelse(p.value < 0.05, "\*", ""),  
 estimate = round(estimate, 3),  
 p.value = round(p.value, 4))  
knitr::kable(results\_df, format = "pandoc", caption = "Ordinal Regression: Likert Attitude")

Ordinal Regression: Likert Attitude

| term | estimate | std.error | statistic | coef.type | p.value | attitude\_item | significant |
| --- | --- | --- | --- | --- | --- | --- | --- |
| KNOWLEDGE\_SCORE | 0.046 | 0.1526709 | 0.3027226 | coefficient | 0.7621 | POPRED\_A |  |
| CONFIDENCE\_SCORE | 0.118 | 0.1708955 | 0.6879437 | coefficient | 0.4915 | POPRED\_A |  |
| DEMO\_EDU\_SCORE | -0.164 | 0.2419691 | -0.6778683 | coefficient | 0.4979 | POPRED\_A |  |
| DEMO\_EXP\_SCORE | 0.023 | 0.2340501 | 0.0969058 | coefficient | 0.9228 | POPRED\_A |  |
| GENDER\_BIN | -0.084 | 0.3713882 | -0.2251749 | coefficient | 0.8218 | POPRED\_A |  |
| AGE\_BIN | 0.508 | 0.3626402 | 1.3995318 | coefficient | 0.1617 | POPRED\_A |  |
| KNOWLEDGE\_SCORE | -0.114 | 0.1564846 | -0.7267492 | coefficient | 0.4674 | POPPLAN\_A |  |
| CONFIDENCE\_SCORE | -0.075 | 0.1780213 | -0.4198277 | coefficient | 0.6746 | POPPLAN\_A |  |
| DEMO\_EDU\_SCORE | 0.034 | 0.2480615 | 0.1373197 | coefficient | 0.8908 | POPPLAN\_A |  |
| DEMO\_EXP\_SCORE | 0.580 | 0.2397924 | 2.4200948 | coefficient | 0.0155 | POPPLAN\_A | \* |
| GENDER\_BIN | -0.249 | 0.3734052 | -0.6679298 | coefficient | 0.5042 | POPPLAN\_A |  |
| AGE\_BIN | 0.064 | 0.3662666 | 0.1744586 | coefficient | 0.8615 | POPPLAN\_A |  |
| KNOWLEDGE\_SCORE | -0.037 | 0.1806880 | -0.2062498 | coefficient | 0.8366 | SURVEY\_A |  |
| CONFIDENCE\_SCORE | -0.301 | 0.2026915 | -1.4832169 | coefficient | 0.1380 | SURVEY\_A |  |
| DEMO\_EDU\_SCORE | 0.505 | 0.2689884 | 1.8764206 | coefficient | 0.0606 | SURVEY\_A |  |
| DEMO\_EXP\_SCORE | -0.299 | 0.2561432 | -1.1656020 | coefficient | 0.2438 | SURVEY\_A |  |
| GENDER\_BIN | -0.460 | 0.4259915 | -1.0800062 | coefficient | 0.2801 | SURVEY\_A |  |
| AGE\_BIN | -0.117 | 0.4030366 | -0.2902450 | coefficient | 0.7716 | SURVEY\_A |  |
| KNOWLEDGE\_SCORE | -0.213 | 0.1591270 | -1.3412736 | coefficient | 0.1798 | VACCINE\_A |  |
| CONFIDENCE\_SCORE | -0.284 | 0.1816485 | -1.5656243 | coefficient | 0.1174 | VACCINE\_A |  |
| DEMO\_EDU\_SCORE | 0.187 | 0.2430438 | 0.7676745 | coefficient | 0.4427 | VACCINE\_A |  |
| DEMO\_EXP\_SCORE | -0.267 | 0.2314076 | -1.1526231 | coefficient | 0.2491 | VACCINE\_A |  |
| GENDER\_BIN | -0.569 | 0.3943355 | -1.4437900 | coefficient | 0.1488 | VACCINE\_A |  |
| AGE\_BIN | -0.858 | 0.3713557 | -2.3108615 | coefficient | 0.0208 | VACCINE\_A | \* |
| KNOWLEDGE\_SCORE | 0.250 | 0.1660911 | 1.5061163 | coefficient | 0.1320 | PREVAL\_A |  |
| CONFIDENCE\_SCORE | -0.099 | 0.1818953 | -0.5442922 | coefficient | 0.5862 | PREVAL\_A |  |
| DEMO\_EDU\_SCORE | -0.297 | 0.2543229 | -1.1678369 | coefficient | 0.2429 | PREVAL\_A |  |
| DEMO\_EXP\_SCORE | 0.162 | 0.2398460 | 0.6770262 | coefficient | 0.4984 | PREVAL\_A |  |
| GENDER\_BIN | -0.417 | 0.3905242 | -1.0672098 | coefficient | 0.2859 | PREVAL\_A |  |
| AGE\_BIN | -0.119 | 0.3668610 | -0.3246218 | coefficient | 0.7455 | PREVAL\_A |  |
| KNOWLEDGE\_SCORE | 0.069 | 0.1716304 | 0.4044990 | coefficient | 0.6858 | DIVERSE\_A |  |
| CONFIDENCE\_SCORE | 0.005 | 0.1902992 | 0.0259282 | coefficient | 0.9793 | DIVERSE\_A |  |
| DEMO\_EDU\_SCORE | 0.152 | 0.2548657 | 0.5951827 | coefficient | 0.5517 | DIVERSE\_A |  |
| DEMO\_EXP\_SCORE | 0.071 | 0.2393376 | 0.2951221 | coefficient | 0.7679 | DIVERSE\_A |  |
| GENDER\_BIN | -0.125 | 0.3905520 | -0.3194153 | coefficient | 0.7494 | DIVERSE\_A |  |
| AGE\_BIN | -0.810 | 0.3803304 | -2.1307816 | coefficient | 0.0331 | DIVERSE\_A | \* |
| KNOWLEDGE\_SCORE | 0.022 | 0.1550861 | 0.1426658 | coefficient | 0.8866 | CONSEQ\_A |  |
| CONFIDENCE\_SCORE | -0.077 | 0.1815854 | -0.4255753 | coefficient | 0.6704 | CONSEQ\_A |  |
| DEMO\_EDU\_SCORE | -0.008 | 0.2479400 | -0.0317769 | coefficient | 0.9746 | CONSEQ\_A |  |
| DEMO\_EXP\_SCORE | -0.058 | 0.2330437 | -0.2471674 | coefficient | 0.8048 | CONSEQ\_A |  |
| GENDER\_BIN | 0.046 | 0.3801449 | 0.1208720 | coefficient | 0.9038 | CONSEQ\_A |  |
| AGE\_BIN | -0.299 | 0.3628402 | -0.8235752 | coefficient | 0.4102 | CONSEQ\_A |  |
| KNOWLEDGE\_SCORE | 0.010 | 0.1497856 | 0.0687750 | coefficient | 0.9452 | CLIMATE\_A |  |
| CONFIDENCE\_SCORE | 0.053 | 0.1790489 | 0.2969011 | coefficient | 0.7665 | CLIMATE\_A |  |
| DEMO\_EDU\_SCORE | 0.017 | 0.2420454 | 0.0706554 | coefficient | 0.9437 | CLIMATE\_A |  |
| DEMO\_EXP\_SCORE | -0.089 | 0.2211984 | -0.4016722 | coefficient | 0.6879 | CLIMATE\_A |  |
| GENDER\_BIN | -1.674 | 0.3931589 | -4.2580849 | coefficient | 0.0000 | CLIMATE\_A | \* |
| AGE\_BIN | -0.794 | 0.3559368 | -2.2304395 | coefficient | 0.0257 | CLIMATE\_A | \* |
| KNOWLEDGE\_SCORE | -0.323 | 0.1836334 | -1.7611869 | coefficient | 0.0782 | EDREQ\_A |  |
| CONFIDENCE\_SCORE | -0.669 | 0.2088386 | -3.2034338 | coefficient | 0.0014 | EDREQ\_A | \* |
| DEMO\_EDU\_SCORE | -0.224 | 0.2664904 | -0.8405872 | coefficient | 0.4006 | EDREQ\_A |  |
| DEMO\_EXP\_SCORE | 0.463 | 0.2556381 | 1.8105609 | coefficient | 0.0702 | EDREQ\_A |  |
| GENDER\_BIN | -1.888 | 0.4659253 | -4.0528683 | coefficient | 0.0001 | EDREQ\_A | \* |
| AGE\_BIN | -0.500 | 0.3994255 | -1.2508842 | coefficient | 0.2110 | EDREQ\_A |  |
| KNOWLEDGE\_SCORE | 0.211 | 0.1716486 | 1.2303331 | coefficient | 0.2186 | INFO\_A |  |
| CONFIDENCE\_SCORE | 0.176 | 0.1909426 | 0.9238095 | coefficient | 0.3556 | INFO\_A |  |
| DEMO\_EDU\_SCORE | 0.279 | 0.2473526 | 1.1263805 | coefficient | 0.2600 | INFO\_A |  |
| DEMO\_EXP\_SCORE | -0.250 | 0.2316925 | -1.0811732 | coefficient | 0.2796 | INFO\_A |  |
| GENDER\_BIN | -0.454 | 0.3837758 | -1.1822889 | coefficient | 0.2371 | INFO\_A |  |
| AGE\_BIN | 0.244 | 0.3699571 | 0.6588214 | coefficient | 0.5100 | INFO\_A |  |
| KNOWLEDGE\_SCORE | -0.006 | 0.1559630 | -0.0358060 | coefficient | 0.9714 | HANDSON\_A |  |
| CONFIDENCE\_SCORE | -0.046 | 0.1767659 | -0.2606140 | coefficient | 0.7944 | HANDSON\_A |  |
| DEMO\_EDU\_SCORE | 0.344 | 0.2438855 | 1.4116398 | coefficient | 0.1581 | HANDSON\_A |  |
| DEMO\_EXP\_SCORE | -0.056 | 0.2157980 | -0.2603649 | coefficient | 0.7946 | HANDSON\_A |  |
| GENDER\_BIN | -0.924 | 0.3940317 | -2.3445333 | coefficient | 0.0191 | HANDSON\_A | \* |
| AGE\_BIN | 0.575 | 0.3613928 | 1.5913064 | coefficient | 0.1115 | HANDSON\_A |  |
| KNOWLEDGE\_SCORE | 0.240 | 0.1641111 | 1.4595795 | coefficient | 0.1444 | CWDAL\_A |  |
| CONFIDENCE\_SCORE | -0.082 | 0.1817906 | -0.4500944 | coefficient | 0.6526 | CWDAL\_A |  |
| DEMO\_EDU\_SCORE | 0.702 | 0.2552398 | 2.7499111 | coefficient | 0.0060 | CWDAL\_A | \* |
| DEMO\_EXP\_SCORE | 0.154 | 0.2411006 | 0.6383847 | coefficient | 0.5232 | CWDAL\_A |  |
| GENDER\_BIN | 0.635 | 0.3871257 | 1.6409439 | coefficient | 0.1008 | CWDAL\_A |  |
| AGE\_BIN | -0.364 | 0.3647407 | -0.9984598 | coefficient | 0.3181 | CWDAL\_A |  |
| KNOWLEDGE\_SCORE | -0.053 | 0.1516175 | -0.3480363 | coefficient | 0.7278 | BATS\_A |  |
| CONFIDENCE\_SCORE | -0.145 | 0.1743156 | -0.8342540 | coefficient | 0.4041 | BATS\_A |  |
| DEMO\_EDU\_SCORE | -0.314 | 0.2428933 | -1.2926599 | coefficient | 0.1961 | BATS\_A |  |
| DEMO\_EXP\_SCORE | 0.117 | 0.2269726 | 0.5169507 | coefficient | 0.6052 | BATS\_A |  |
| GENDER\_BIN | -0.079 | 0.3901013 | -0.2025994 | coefficient | 0.8394 | BATS\_A |  |
| AGE\_BIN | -0.378 | 0.3617988 | -1.0453374 | coefficient | 0.2959 | BATS\_A |  |
| KNOWLEDGE\_SCORE | -0.107 | 0.1610116 | -0.6624909 | coefficient | 0.5077 | PPEREQ\_A |  |
| CONFIDENCE\_SCORE | -0.213 | 0.1801502 | -1.1815872 | coefficient | 0.2374 | PPEREQ\_A |  |
| DEMO\_EDU\_SCORE | -0.062 | 0.2496120 | -0.2472691 | coefficient | 0.8047 | PPEREQ\_A |  |
| DEMO\_EXP\_SCORE | 0.076 | 0.2295434 | 0.3326425 | coefficient | 0.7394 | PPEREQ\_A |  |
| GENDER\_BIN | 0.034 | 0.3775691 | 0.0912280 | coefficient | 0.9273 | PPEREQ\_A |  |
| AGE\_BIN | 0.038 | 0.3616897 | 0.1037367 | coefficient | 0.9174 | PPEREQ\_A |  |
| KNOWLEDGE\_SCORE | 0.043 | 0.1597092 | 0.2710543 | coefficient | 0.7863 | EHD\_A |  |
| CONFIDENCE\_SCORE | -0.409 | 0.1848928 | -2.2147242 | coefficient | 0.0268 | EHD\_A | \* |
| DEMO\_EDU\_SCORE | 0.142 | 0.2462661 | 0.5781986 | coefficient | 0.5631 | EHD\_A |  |
| DEMO\_EXP\_SCORE | 0.565 | 0.2382302 | 2.3728513 | coefficient | 0.0177 | EHD\_A | \* |
| GENDER\_BIN | -0.189 | 0.3927807 | -0.4799296 | coefficient | 0.6313 | EHD\_A |  |
| AGE\_BIN | 0.268 | 0.3668734 | 0.7300835 | coefficient | 0.4653 | EHD\_A |  |
| KNOWLEDGE\_SCORE | -0.072 | 0.1631410 | -0.4393815 | coefficient | 0.6604 | DARWIN\_A |  |
| CONFIDENCE\_SCORE | -0.443 | 0.1881635 | -2.3563655 | coefficient | 0.0185 | DARWIN\_A | \* |
| DEMO\_EDU\_SCORE | 0.538 | 0.2666168 | 2.0188130 | coefficient | 0.0435 | DARWIN\_A | \* |
| DEMO\_EXP\_SCORE | 0.095 | 0.2362477 | 0.4017271 | coefficient | 0.6879 | DARWIN\_A |  |
| GENDER\_BIN | -1.533 | 0.4310289 | -3.5565561 | coefficient | 0.0004 | DARWIN\_A | \* |
| AGE\_BIN | 0.125 | 0.3859707 | 0.3249493 | coefficient | 0.7452 | DARWIN\_A |  |

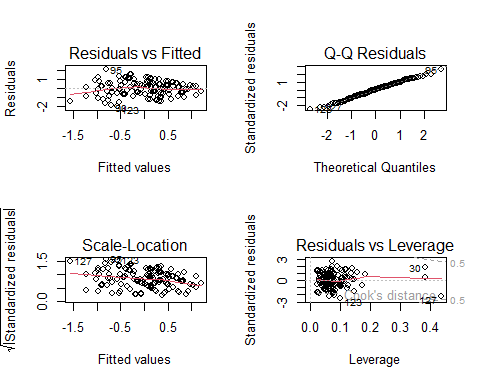
write.csv(results\_df, file.path(oup, "ordinalattitudes\_results.csv"), row.names = FALSE)

# 5 Results

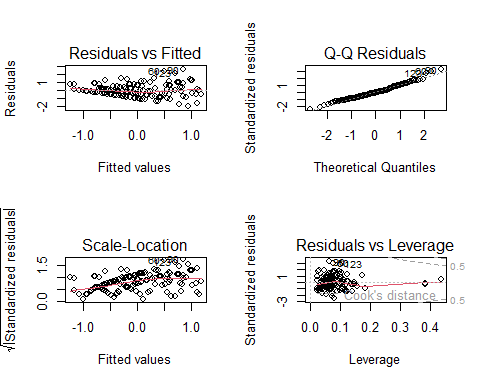
require(sjPlot)  
require(car)  
require(modelsummary)  
require(stargazer)  
require(ggeffects)  
require(effects)  
require(ggplot2)

#### 5.0.0.1 Diagnostics

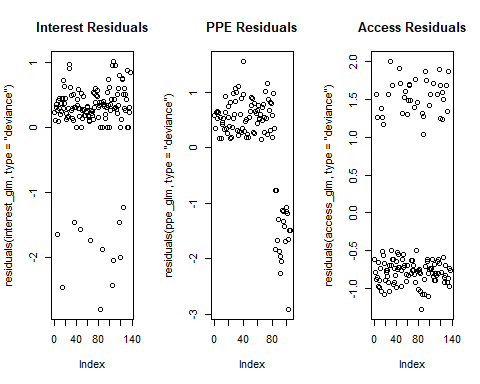
# Residual plots ------------------------  
par(mfrow = c(2, 2))  
plot(know\_lm)



plot(conf\_lm)



# GLM diagnostics (deviance residuals, etc.)  
par(mfrow = c(1, 3))  
plot(residuals(interest\_glm, type = "deviance"), main = "Interest Residuals")  
plot(residuals(ppe\_glm, type = "deviance"), main = "PPE Residuals")  
plot(residuals(access\_glm, type = "deviance"), main = "Access Residuals")

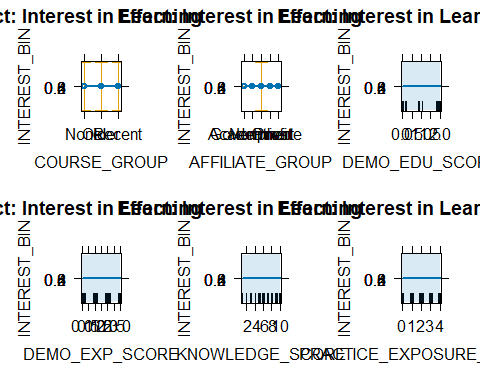


# VIF --------------------------------  
vif\_results <- list(  
 "Knowledge" = vif(know\_lm),  
 "Confidence" = vif(conf\_lm),  
 "Interest" = vif(interest\_glm),  
 "PPE" = vif(ppe\_glm),  
 "Access" = vif(access\_glm))  
print(vif\_results)

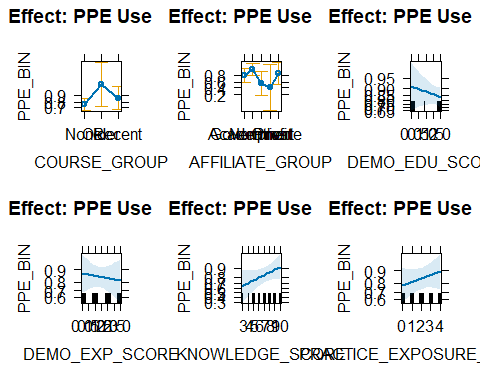
## $Knowledge  
## GVIF Df GVIF^(1/(2\*Df))  
## COURSE\_GROUP 1.242355 2 1.055751  
## AFFILIATE\_GROUP 1.286867 4 1.032029  
## PRACTICE\_EXPOSURE\_SCORE 1.142748 1 1.068994  
## ATT\_CONCERN\_SCORE 1.116708 1 1.056744  
## ATT\_MISINFO\_SCORE 1.117966 1 1.057339  
## INTEREST\_BIN 1.106923 1 1.052104  
##   
## $Confidence  
## GVIF Df GVIF^(1/(2\*Df))  
## COURSE\_GROUP 1.242355 2 1.055751  
## AFFILIATE\_GROUP 1.286867 4 1.032029  
## PRACTICE\_EXPOSURE\_SCORE 1.142748 1 1.068994  
## ATT\_CONCERN\_SCORE 1.116708 1 1.056744  
## ATT\_MISINFO\_SCORE 1.117966 1 1.057339  
## INTEREST\_BIN 1.106923 1 1.052104  
##   
## $Interest  
## GVIF Df GVIF^(1/(2\*Df))  
## COURSE\_GROUP 1.245739 2 1.056469  
## AFFILIATE\_GROUP 1.753168 4 1.072699  
## DEMO\_EDU\_SCORE 1.827502 1 1.351851  
## DEMO\_EXP\_SCORE 1.697180 1 1.302758  
## KNOWLEDGE\_SCORE 1.211996 1 1.100907  
## PRACTICE\_EXPOSURE\_SCORE 1.125875 1 1.061072  
##   
## $PPE  
## GVIF Df GVIF^(1/(2\*Df))  
## COURSE\_GROUP 1.299371 2 1.067661  
## AFFILIATE\_GROUP 1.869071 4 1.081317  
## DEMO\_EDU\_SCORE 1.562761 1 1.250104  
## DEMO\_EXP\_SCORE 1.730427 1 1.315457  
## KNOWLEDGE\_SCORE 1.129689 1 1.062868  
## PRACTICE\_EXPOSURE\_SCORE 1.170638 1 1.081960  
##   
## $Access  
## DEMO\_EDU\_SCORE DEMO\_EXP\_SCORE KNOWLEDGE\_SCORE   
## 1.363956 1.430018 1.139369   
## PRACTICE\_EXPOSURE\_SCORE   
## 1.031606

#### 5.0.0.2 Effects Plots

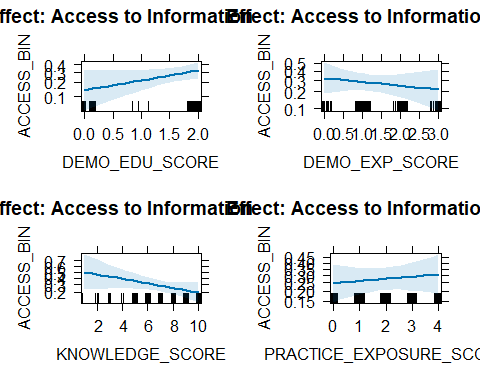
plot(allEffects(interest\_glm), main = "Effect: Interest in Learning")



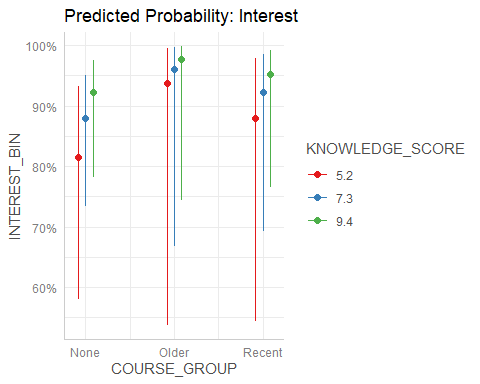
plot(allEffects(ppe\_glm), main = "Effect: PPE Use")



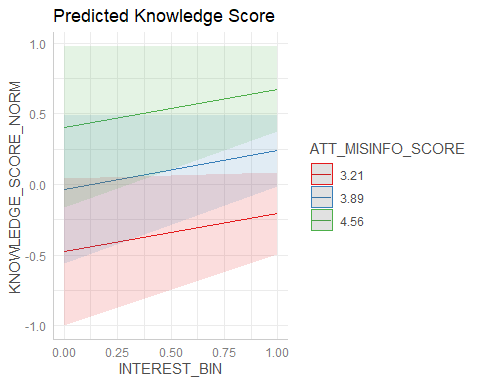
plot(allEffects(access\_glm), main = "Effect: Access to Information")



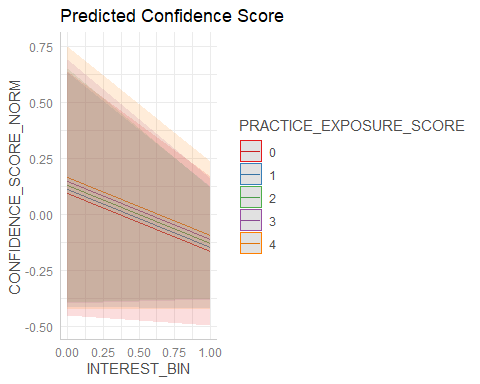
# GGPREDICT: Predicted values with ggtitle() ---------------------------------  
  
# Logistic: Interest Model  
interestgp <- ggpredict(interest\_glm, terms = c("COURSE\_GROUP", "KNOWLEDGE\_SCORE"))  
plot(interestgp) + ggtitle("Predicted Probability: Interest")



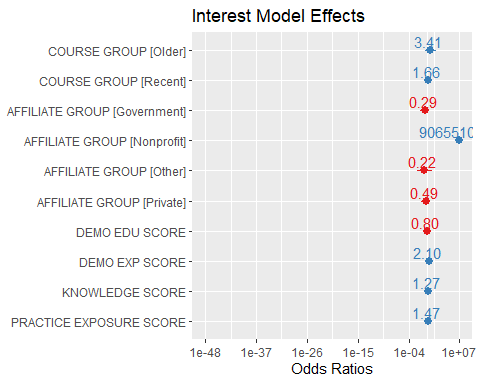
# Linear: Knowledge Model  
knowgp <- ggpredict(know\_lm, terms = c("INTEREST\_BIN", "ATT\_MISINFO\_SCORE"))  
plot(knowgp) + ggtitle("Predicted Knowledge Score")



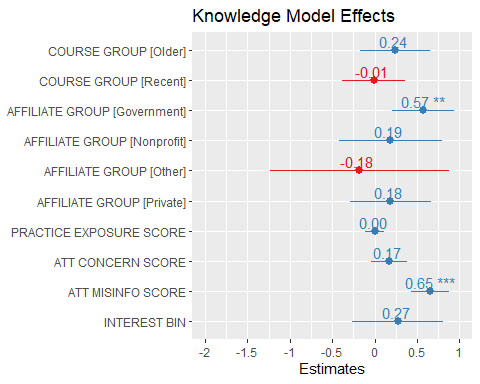
# Linear: Confidence Model  
confgp <- ggpredict(conf\_lm, terms = c("INTEREST\_BIN", "PRACTICE\_EXPOSURE\_SCORE"))  
plot(confgp) + ggtitle("Predicted Confidence Score")



# SJPlot: Visualize model coefficients ----------------------------------------  
  
# GLM: Interest Model Coefficient Plot  
plot\_model(interest\_glm, type = "est", show.values = TRUE, value.offset = 0.3) +  
 ggtitle("Interest Model Effects")



# LM: Knowledge Model Coefficient Plot  
plot\_model(know\_lm, type = "est", show.values = TRUE, value.offset = 0.3) +  
 ggtitle("Knowledge Model Effects")



# Side-by-side table comparison  
tab\_model(  
 know\_lm, conf\_lm, interest\_glm, ppe\_glm, access\_glm,  
 show.ci = TRUE, show.se = TRUE, show.stat = TRUE,  
 title = "Model Comparison Table")

Model Comparison Table

KNOWLEDGE SCORE NORM

CONFIDENCE SCORE NORM

INTEREST BIN

PPE BIN

ACCESS BIN

Predictors

Estimates

std. Error

CI

Statistic

p

Estimates

std. Error

CI

Statistic

p

Odds Ratios

std. Error

CI

Statistic

p

Odds Ratios

std. Error

CI

Statistic

p

Odds Ratios

std. Error

CI

Statistic

p

(Intercept)

-3.70

0.63

-Inf – Inf

-5.90

<0.001

4.08

0.62

-Inf – Inf

6.58

<0.001

1.20

1.54

0.00 – Inf

0.14

0.886

0.51

0.72

0.00 – Inf

-0.48

0.631

0.56

0.43

0.00 – Inf

-0.75

0.451

COURSE GROUP [Older]

0.24

0.21

-Inf – Inf

1.16

0.249

-0.32

0.21

-Inf – Inf

-1.53

0.128

3.41

4.51

0.00 – Inf

0.93

0.354

8.49

10.77

0.00 – Inf

1.69

0.091

COURSE GROUP [Recent]

-0.01

0.19

-Inf – Inf

-0.05

0.960

-0.13

0.19

-Inf – Inf

-0.69

0.489

1.66

1.47

0.00 – Inf

0.57

0.569

1.92

1.35

0.00 – Inf

0.93

0.351

AFFILIATE GROUP[Government]

0.57

0.18

-Inf – Inf

3.07

0.003

-0.57

0.18

-Inf – Inf

-3.11

0.002

0.29

0.26

0.00 – Inf

-1.39

0.164

2.38

1.51

0.00 – Inf

1.37

0.171

AFFILIATE GROUP[Nonprofit]

0.19

0.31

-Inf – Inf

0.61

0.545

-0.16

0.30

-Inf – Inf

-0.51

0.609

9065510.16

17055579457.39

0.00 – Inf

0.01

0.993

0.33

0.33

0.00 – Inf

-1.12

0.262

AFFILIATE GROUP [Other]

-0.18

0.53

-Inf – Inf

-0.34

0.734

-1.07

0.53

-Inf – Inf

-2.03

0.045

0.22

0.38

0.00 – Inf

-0.88

0.379

0.19

0.32

0.00 – Inf

-0.97

0.332

AFFILIATE GROUP [Private]

0.18

0.24

-Inf – Inf

0.76

0.449

-0.34

0.24

-Inf – Inf

-1.42

0.158

0.49

0.56

0.00 – Inf

-0.62

0.534

1.32

1.17

0.00 – Inf

0.31

0.754

PRACTICE EXPOSURE SCORE

0.00

0.06

-Inf – Inf

0.01

0.990

0.02

0.05

-Inf – Inf

0.32

0.752

1.47

0.38

0.00 – Inf

1.49

0.137

1.23

0.26

0.00 – Inf

0.98

0.325

1.08

0.15

0.00 – Inf

0.56

0.573

ATT CONCERN SCORE

0.17

0.11

-Inf – Inf

1.57

0.120

-0.22

0.11

-Inf – Inf

-2.11

0.037

ATT MISINFO SCORE

0.65

0.11

-Inf – Inf

5.76

<0.001

-0.69

0.11

-Inf – Inf

-6.13

<0.001

INTEREST BIN

0.27

0.27

-Inf – Inf

1.00

0.317

-0.26

0.27

-Inf – Inf

-0.96

0.338

DEMO EDU SCORE

0.80

0.37

0.00 – Inf

-0.49

0.624

0.68

0.31

0.00 – Inf

-0.85

0.396

1.73

0.54

0.00 – Inf

1.75

0.080

DEMO EXP SCORE

2.10

1.10

0.00 – Inf

1.41

0.158

0.86

0.33

0.00 – Inf

-0.40

0.688

0.83

0.22

0.00 – Inf

-0.71

0.475

KNOWLEDGE SCORE

1.27

0.21

0.00 – Inf

1.45

0.147

1.27

0.20

0.00 – Inf

1.53

0.126

0.85

0.08

0.00 – Inf

-1.63

0.103

Observations

137

137

137

105

137

R2 / R2 adjusted

0.339 / 0.286

0.360 / 0.310

0.130

0.190

0.046

#### 5.0.0.3 Export

modelsummary(  
 list(  
 "Knowledge" = know\_lm,  
 "Confidence" = conf\_lm,  
 "Interest" = interest\_glm,  
 "PPE Use" = ppe\_glm,  
 "Access" = access\_glm),  
 statistic = "conf.int",  
 output = file.path(oup, "regression\_results.docx"))  
  
# Linear & logistic combined   
stargazer(  
 know\_lm, conf\_lm, interest\_glm, ppe\_glm, access\_glm,  
 type = "text",  
 title = "KAP Regression Models",  
 out = file.path(oup, "regression\_results.txt"),  
 single.row = TRUE,  
 digits = 3,  
 covariate.labels = NULL,  
 omit.stat = c("f", "ser"))

##   
## KAP Regression Models  
## =====================================================================================================================  
## Dependent variable:   
## -------------------------------------------------------------------------------------------  
## KNOWLEDGE\_SCORE\_NORM CONFIDENCE\_SCORE\_NORM INTEREST\_BIN PPE\_BIN ACCESS\_BIN   
## OLS OLS logistic logistic logistic   
## (1) (2) (3) (4) (5)   
## ---------------------------------------------------------------------------------------------------------------------  
## COURSE\_GROUPOlder 0.241 (0.208) -0.316 (0.206) 1.227 (1.323) 2.139\* (1.268)   
## COURSE\_GROUPRecent -0.010 (0.188) -0.129 (0.186) 0.505 (0.886) 0.654 (0.701)   
## AFFILIATE\_GROUPGovernment 0.568\*\*\* (0.185) -0.568\*\*\* (0.183) -1.254 (0.900) 0.867 (0.634)   
## AFFILIATE\_GROUPNonprofit 0.186 (0.306) -0.155 (0.302) 16.020 (1,881.370) -1.113 (0.991)   
## AFFILIATE\_GROUPOther -0.182 (0.534) -1.070\*\* (0.528) -1.534 (1.743) -1.676 (1.726)   
## AFFILIATE\_GROUPPrivate 0.183 (0.241) -0.338 (0.238) -0.715 (1.151) 0.278 (0.888)   
## DEMO\_EDU\_SCORE -0.228 (0.466) -0.382 (0.450) 0.546\* (0.312)  
## DEMO\_EXP\_SCORE 0.740 (0.524) -0.155 (0.385) -0.186 (0.261)  
## KNOWLEDGE\_SCORE 0.239 (0.165) 0.242 (0.158) -0.160 (0.098)  
## PRACTICE\_EXPOSURE\_SCORE 0.001 (0.056) 0.017 (0.055) 0.384 (0.258) 0.209 (0.213) 0.079 (0.140)   
## ATT\_CONCERN\_SCORE 0.168 (0.107) -0.224\*\* (0.106)   
## ATT\_MISINFO\_SCORE 0.653\*\*\* (0.113) -0.686\*\*\* (0.112)   
## INTEREST\_BIN 0.270 (0.269) -0.256 (0.266)   
## Constant -3.704\*\*\* (0.627) 4.078\*\*\* (0.620) 0.184 (1.280) -0.678 (1.411) -0.577 (0.766)  
## ---------------------------------------------------------------------------------------------------------------------  
## Observations 137 137 137 105 137   
## R2 0.339 0.360   
## Adjusted R2 0.286 0.310   
## Log Likelihood -33.301 -44.752 -78.813   
## Akaike Inf. Crit. 88.602 111.505 167.626   
## =====================================================================================================================  
## Note: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

#### 5.0.0.4 References

# ----to display the packages within the .qmd without creating another .bib -----  
knitr::write\_bib(sub("^package:", "", grep("package", search(), value=TRUE)), file='')

## @Manual{R-base,  
## title = {R: A Language and Environment for Statistical Computing},  
## author = {{R Core Team}},  
## organization = {R Foundation for Statistical Computing},  
## address = {Vienna, Austria},  
## year = {2024},  
## url = {https://www.R-project.org/},  
## }  
##   
## @Manual{R-broom,  
## title = {broom: Convert Statistical Objects into Tidy Tibbles},  
## author = {David Robinson and Alex Hayes and Simon Couch},  
## year = {2024},  
## note = {R package version 1.0.6},  
## url = {https://broom.tidymodels.org/},  
## }  
##   
## @Manual{R-car,  
## title = {car: Companion to Applied Regression},  
## author = {John Fox and Sanford Weisberg and Brad Price},  
## year = {2023},  
## note = {R package version 3.1-2},  
## url = {https://r-forge.r-project.org/projects/car/},  
## }  
##   
## @Manual{R-carData,  
## title = {carData: Companion to Applied Regression Data Sets},  
## author = {John Fox and Sanford Weisberg and Brad Price},  
## year = {2022},  
## note = {R package version 3.0-5},  
## url = {https://r-forge.r-project.org/projects/car/},  
## }  
##   
## @Manual{R-dplyr,  
## title = {dplyr: A Grammar of Data Manipulation},  
## author = {Hadley Wickham and Romain François and Lionel Henry and Kirill Müller and Davis Vaughan},  
## year = {2023},  
## note = {R package version 1.1.4},  
## url = {https://dplyr.tidyverse.org},  
## }  
##   
## @Manual{R-effects,  
## title = {effects: Effect Displays for Linear, Generalized Linear, and Other Models},  
## author = {John Fox and Sanford Weisberg and Brad Price and Michael Friendly and Jangman Hong},  
## year = {2022},  
## note = {R package version 4.2-2},  
## url = {https://www.r-project.org},  
## }  
##   
## @Manual{R-flextable,  
## title = {flextable: Functions for Tabular Reporting},  
## author = {David Gohel and Panagiotis Skintzos},  
## year = {2024},  
## note = {R package version 0.9.6},  
## url = {https://ardata-fr.github.io/flextable-book/},  
## }  
##   
## @Manual{R-forcats,  
## title = {forcats: Tools for Working with Categorical Variables (Factors)},  
## author = {Hadley Wickham},  
## year = {2023},  
## note = {R package version 1.0.0},  
## url = {https://forcats.tidyverse.org/},  
## }  
##   
## @Manual{R-ggeffects,  
## title = {ggeffects: Create Tidy Data Frames of Marginal Effects for ggplot from  
## Model Outputs},  
## author = {Daniel Lüdecke},  
## year = {2025},  
## note = {R package version 2.2.1},  
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## author = {John Fox},  
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## @Article{ggeffects2018,  
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## volume = {3},  
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## author = {Daniel Lüdecke},  
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## title = {ggplot2: Elegant Graphics for Data Analysis},  
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## year = {2016},  
## isbn = {978-3-319-24277-4},  
## url = {https://ggplot2.tidyverse.org},  
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