

biostats_consulting

2024-10-05

Contents

```
library(tidyr)
library(dplyr)
```

```
##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##   filter, lag

## The following objects are masked from 'package:base':
##
##   intersect, setdiff, setequal, union
```

```
library(readr)
library(summarytools)
library(ggplot2)
library(gridExtra)
```

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

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

```
library(stringr)
library(Rtsne)
library(reshape2)
```

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

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

```
library(car)
```

```
## Loading required package: carData
```

```
##
```

```
## Attaching package: 'car'
```

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

```
##
```

```
##      recode
```

```
# Load the dataset
```

```
data_2022 <- read_csv("S:\\biostats_consulting_lab\\cleaned_2022_survey_dta.csv")
```

```
## Rows: 1423 Columns: 17
```

```
## -- Column specification -----
```

```
## Delimiter: ","
```

```
## chr  (14): consent, availability, sec1_q4, sec1_q5, sec1_q6, sec1_q7, sec1_q...
```

```
## dbl  (2): caseid, sec11_start
```

```
## date (1): sec1_q1
```

```
##
```

```
## i Use `spec()` to retrieve the full column specification for this data.
```

```
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```
data_2024 <- read_csv("S:\\biostats_consulting_lab\\cleaned_2024_survey_dta.csv")
```

```
## Rows: 1405 Columns: 32
```

```
## -- Column specification -----
```

```
## Delimiter: ","
```

```
## chr  (27): response_1, response_2, response_3, phone_rel, resp_relationship...
```

```
## dbl  (2): caseid, phone_response
```

```
## lgl  (1): religion_oth
```

```
## date (2): birthdate, survey_date
```

```
##
```

```
## i Use `spec()` to retrieve the full column specification for this data.
```

```
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```
# Rename the specified variables and clean data_2022
```

```
data_2022_cleaned <- data_2022 %>%
```

```
  rename(
```

```
    dob = sec1_q1,
```

```
    gender = sec1_q4,
```

```
    highest_education = sec1_q5,
```

```
    employment_status = sec1_q6,
```

```
    marital_status = sec1_q7,
```

```
    household_income = sec1_q8,
```

```
    residence_area = sec1_q9,
```

```
    survey_location = sec1_q10,
```

```
    survey_duration = sec11_start,
```

```
    religious = sec11_q156,
```

```

religion = sec11_q157,
specified_other_religion = sec11_q157other,
science_contradict = sec11_q158,
science_or_religion = sec11_q159
) %>%
select(-consent, -availability) %>%
mutate(
  religion = case_when(
    religion %in% c("CCAP", "Traditional African religion") ~ "Other",
    religion %in% c("Seventh Day Adventist") ~ "Other Christian",
    religion == "Prefer not to answer" ~ "Prefer not to answer [do not read aloud]",
    TRUE ~ religion
  ),
  employment_status = if_else(is.na(employment_status), "Missing", employment_status)
)

```

```

data_2022_cleaned <- data_2022_cleaned %>%
  mutate(across(c(religion, science_or_religion, science_contradict, religious),
    ~ replace_na(., "Missing")))

```

Clean and rename specified variables in data_2024

```
data_2024_cleaned <- data_2024 %>%
```

Rename variables

```

rename(
  caseid = caseid,
  response_status = response_1,
  response_by = response_2,
  dob = birthdate,
  highest_education = educ_level,
  employment_status = employ_status,
  people_speak_to_daily = number_people,
  household_income = hh_income,
  specified_other_religion = religion_oth,
  call_status = call_status
) %>%

```

Select only the relevant variables

```

select(
  dob, caseid, response_status, response_by, gender, highest_education, marital_status, parent_guardian,
  employment_status, work_industry, people_speak_to_daily,
  household_income, residence_area, religion,
  specified_other_religion, call_status, survey_date
) %>%

```

Clean data by re-coding and handling missing values

```
mutate(
```

Re-code religion variable by grouping similar categories

```

religion = case_when(
  religion %in% c("Seventh Day Adventists", "Apostolic/New Apostlic Church", "Church of Christ",
    "Gospel/New Testament/Injili Church", "Salvation Army Church", "Assembly of God Church",
    "Roho Church", "Church of God", "Jehovah's Witness", "Legio Maria Church", "NENO",
    "Repentance and Holiness", "Pentecostal/ Protestant Church") ~ "Other Christian",
  religion == "Prefer not to answer [do not read aloud]" ~ "Prefer not to answer",

```

```

    religion == "Akorino" ~ "Other",
    religion == "Baptist Church" ~ "Baptist",
    TRUE ~ religion
  ),

  # Re-code employment_status variable
  employment_status = case_when(
    employment_status %in% c("Self-employed (includes agribusiness)", "Peasant farmer") ~ "Self-employed",
    TRUE ~ employment_status
  ),
  highest_education = case_when(
    highest_education == "Prefer not to answer" ~ "Prefer not to answer [do not read aloud]",
    TRUE ~ highest_education
  )
) %>%

# Replace NA values in highest_education with "Missing"
mutate(highest_education = replace_na(highest_education, "Missing")) %>%
mutate(marital_status = replace_na(marital_status, "Missing")) %>%
mutate(parent_guardian = replace_na(parent_guardian, "Missing")) %>%
mutate(work_industry = replace_na(work_industry, "Missing")) %>%
mutate(people_speak_to_daily = replace_na(people_speak_to_daily, "Missing")) %>%
mutate(household_income = replace_na(household_income, "Missing")) %>%
mutate(residence_area = replace_na(residence_area, "Missing")) %>%
mutate(employment_status = replace_na(employment_status, "Missing")) %>%
mutate(religion = replace_na(religion, "Missing"))

data_2024_cleaned <- data_2024_cleaned %>%
  left_join(data_2022_cleaned %>% select(caseid, gender, religion, dob), by = "caseid", suffix = c("_2022", "_2024")) %>%
  mutate(
    # 2024 gender NA 2022 gender
    gender_2024 = coalesce(gender_2024, gender_2022),
    # gender NA "Unknown"
    gender_2024 = replace_na(gender_2024, "Unknown"),

    dob_2024 = coalesce(dob_2024, dob_2022),
    # religion NA "Unknown"
    dob_2024 = replace_na(dob_2024, "Unknown")
  ) %>%

  # gender_2022 religion_2022 gender_2024 religion_2024
  select(-gender_2022, -dob_2022) %>%
  rename(gender = gender_2024, dob = dob_2024)

# Replace "Prefer not to answer [do not read aloud]" with "Prefer not to answer" across all columns
data_2024_cleaned <- data_2024_cleaned %>%
  mutate(across(everything(), ~str_replace(., "Prefer not to answer \\[do not read aloud\\]", "Prefer not to answer")))
data_2022_cleaned <- data_2022_cleaned %>%
  mutate(across(everything(), ~str_replace(., "Prefer not to answer \\[do not read aloud\\]", "Prefer not to answer")))

```

```
# Display the first few rows of the cleaned datasets
head(data_2022_cleaned)
```

```
## # A tibble: 6 x 15
##   caseid dob      gender highest_education employment_status marital_status
##   <chr> <chr>    <chr> <chr>          <chr>          <chr>
## 1 1012  1993-07-04 Male   Secondary      Casual laborer   Divorced/Sepa~
## 2 1054  1992-02-04 Female Primary       Not employed and no~ Married
## 3 1182  1984-08-17 Female Higher       Not employed but lo~ Married
## 4 1220  1992-06-23 Male   Higher         Self-employed    Married
## 5 1223  1975-01-01 Female Secondary   Self-employed    Married
## 6 1255  1982-09-23 Female Higher      Employed full-time Married
## # i 9 more variables: household_income <chr>, residence_area <chr>,
## #   survey_location <chr>, survey_duration <chr>, religious <chr>,
## #   religion <chr>, specified_other_religion <chr>, science_contradict <chr>,
## #   science_or_religion <chr>
```

```
head(data_2024_cleaned)
```

```
## # A tibble: 6 x 18
##   dob      caseid response_status      response_by gender highest_education
##   <chr>    <chr>    <chr>          <chr>        <chr> <chr>
## 1 1998-11-09 10003 Answered the phone, co~ <NA>        Female Secondary
## 2 1974-06-06 10048 Answered the phone, co~ <NA>        Female Secondary
## 3 1994-06-30 10077 Answered the phone, co~ <NA>        Female Primary
## 4 1969-07-07 10086 Answered the phone, co~ <NA>        Male   Higher
## 5 1995-08-08 10088 Number does not work (~ <NA>        Male   Missing
## 6 1982-01-01 10119 Answered the phone, co~ <NA>        Female Missing
## # i 12 more variables: marital_status <chr>, parent_guardian <chr>,
## #   employment_status <chr>, work_industry <chr>, people_speak_to_daily <chr>,
## #   household_income <chr>, residence_area <chr>, religion_2024 <chr>,
## #   specified_other_religion <chr>, call_status <chr>, survey_date <chr>,
## #   religion_2022 <chr>
```

```
# Check for missing values in both datasets
```

```
missing_values_2022 <- sapply(data_2022_cleaned, function(x) sum(is.na(x)))
missing_values_2024 <- sapply(data_2024_cleaned, function(x) sum(is.na(x)))
print(missing_values_2022)
```

```
##           caseid           dob           gender
##           0           0           0
## highest_education employment_status marital_status
##           0           0           0
## household_income residence_area survey_location
##           0           0           0
## survey_duration religious religion
##           29           0           0
## specified_other_religion science_contradict science_or_religion
##           1421           0           0
```

```
print(missing_values_2024)
```

```
##           dob           caseid      response_status
##           0             0             0
##      response_by      gender      highest_education
##      1367             0             0
##      marital_status      parent_guardian      employment_status
##           0             0             0
##      work_industry      people_speak_to_daily      household_income
##           0             0             0
##      residence_area      religion_2024      specified_other_religion
##           0             0             1405
##      call_status      survey_date      religion_2022
##           0             1             0
```

```
# Get summary statistics for both datasets
```

```
summary(data_2022_cleaned)
```

```
##      caseid      dob      gender      highest_education
## Length:1423      Length:1423      Length:1423      Length:1423
## Class :character      Class :character      Class :character      Class :character
## Mode :character      Mode :character      Mode :character      Mode :character
## employment_status      marital_status      household_income      residence_area
## Length:1423      Length:1423      Length:1423      Length:1423
## Class :character      Class :character      Class :character      Class :character
## Mode :character      Mode :character      Mode :character      Mode :character
## survey_location      survey_duration      religious      religion
## Length:1423      Length:1423      Length:1423      Length:1423
## Class :character      Class :character      Class :character      Class :character
## Mode :character      Mode :character      Mode :character      Mode :character
## specified_other_religion      science_contradict      science_or_religion
## Length:1423      Length:1423      Length:1423
## Class :character      Class :character      Class :character
## Mode :character      Mode :character      Mode :character
```

```
summary(data_2024_cleaned)
```

```
##      dob      caseid      response_status      response_by
## Length:1405      Length:1405      Length:1405      Length:1405
## Class :character      Class :character      Class :character      Class :character
## Mode :character      Mode :character      Mode :character      Mode :character
##      gender      highest_education      marital_status      parent_guardian
## Length:1405      Length:1405      Length:1405      Length:1405
## Class :character      Class :character      Class :character      Class :character
## Mode :character      Mode :character      Mode :character      Mode :character
## employment_status      work_industry      people_speak_to_daily      household_income
## Length:1405      Length:1405      Length:1405      Length:1405
## Class :character      Class :character      Class :character      Class :character
## Mode :character      Mode :character      Mode :character      Mode :character
## residence_area      religion_2024      specified_other_religion
## Length:1405      Length:1405      Length:1405
## Class :character      Class :character      Class :character
```

```
## Mode :character      Mode :character      Mode :character
## call_status          survey_date           religion_2022
## Length:1405          Length:1405           Length:1405
## Class :character      Class :character      Class :character
## Mode :character      Mode :character      Mode :character

# Check case IDs in both datasets
caseid_2022 <- data_2022_cleaned$caseid
caseid_2024 <- data_2024_cleaned$caseid

# Filter the 2024 dataset to only include those who successfully followed up
successful_followup_2024 <- data_2024_cleaned %>%
  filter(response_status == "Answered the phone, correct respondent" & call_status == "Completed")

# Extract the case IDs of the successfully followed-up participants
caseid_successful_followup <- successful_followup_2024$caseid

# Identify participants present in both 2022 and successfully followed up in 2024
common_successful_followup <- intersect(caseid_2022, caseid_successful_followup)

# Identify participants in 2022 but not in the successfully followed-up group in 2024 (dropped out)
dropped_participants <- setdiff(caseid_2022, caseid_successful_followup)

# Identify participants in 2024 (successfully followed up) but not in 2022 (new participants)
new_participants <- setdiff(caseid_successful_followup, caseid_2022)

# Output the counts
cat("Number of participants successfully followed up in 2024: ", length(common_successful_followup), "\n")

## Number of participants successfully followed up in 2024: 1096

cat("Number of participants who dropped out after 2022: ", length(dropped_participants), "\n")

## Number of participants who dropped out after 2022: 327

cat("Number of new participants who joined in 2024: ", length(new_participants), "\n")

## Number of new participants who joined in 2024: 0

# View unique values for key variables across both datasets
list(
  religion_2022 = unique(data_2022_cleaned$religion),
  religion_2024 = unique(data_2024_cleaned$religion_2024),
  highest_education_2022 = unique(data_2022_cleaned$highest_education),
  highest_education_2024 = unique(data_2024_cleaned$highest_education),
  employment_status_2022 = unique(data_2022_cleaned$employment_status),
  employment_status_2024 = unique(data_2024_cleaned$employment_status),
  marital_status_2022 = unique(data_2022_cleaned$marital_status),
  marital_status_2024 = unique(data_2024_cleaned$marital_status)
)
```

```

## $religion_2022
## [1] "Other Christian"      "Anglican"           "Catholic"
## [4] "Muslim"              "Other"              "Missing"
## [7] "Baptist"             "Prefer not to answer"
##
## $religion_2024
## [1] "Other Christian"      "Catholic"           "Missing"
## [4] "Muslim"              "Anglican"           "Prefer not to answer"
## [7] "No Religion"         "Baptist"            "Other"
##
## $highest_education_2022
## [1] "Secondary"           "Primary"
## [3] "Higher"             "No school/Did not complete primary"
##
## $highest_education_2024
## [1] "Secondary"           "Primary"
## [3] "Higher"             "Missing"
## [5] "No school/Did not complete primary" "Prefer not to answer"
##
## $employment_status_2022
## [1] "Casual laborer"
## [2] "Not employed and not looking for work"
## [3] "Not employed but looking for work"
## [4] "Self-employed"
## [5] "Employed full-time"
## [6] "Employed part-time"
## [7] "Prefer not to answer"
##
## $employment_status_2024
## [1] "Employed part-time"
## [2] "Self-employed"
## [3] "Not employed but looking for work"
## [4] "Employed full-time"
## [5] "Missing"
## [6] "Casual laborer"
## [7] "Not employed and not looking for work"
## [8] "Prefer not to answer"
##
## $marital_status_2022
## [1] "Divorced/Separated"  "Married"           "Single"
## [4] "Widowed"            "Cohabiting/Partnered" "Prefer not to answer"
##
## $marital_status_2024
## [1] "Single"              "Married"           "Missing"
## [4] "Widowed"            "Divorced/Separated" "Prefer not to answer"
## [7] "Cohabiting/Partnered"

```

```

data_2022_cleaned <- data_2022_cleaned %>%
  semi_join(data_2024_cleaned, by = "caseid") # 2024 caseid

data_2024_cleaned <- data_2024_cleaned %>%
  semi_join(data_2022_cleaned, by = "caseid") # 2022 caseid

```



```

# Function to calculate percentage of missing values
calculate_missing_percentage <- function(data) {
  data %>%
    summarise(across(everything(), ~ sum(. == "Missing") / n() * 100)) %>%
    pivot_longer(cols = everything(), names_to = "variable", values_to = "missing_percentage")
}

# Calculate missing percentages for both datasets
missing_2022 <- calculate_missing_percentage(data_2022_cleaned)
missing_2024 <- calculate_missing_percentage(data_2024_cleaned)

# Plot missing values for data_2022_cleaned
plot_2022 <- ggplot(missing_2022, aes(x = reorder(variable, -missing_percentage), y = missing_percentage)) +
  geom_bar(stat = "identity", fill = "red") +
  coord_flip() +
  labs(title = "Percentage of Missing Values in data_2022_cleaned", x = "Variables", y = "Missing Percentage") +
  theme_minimal()

# Plot missing values for data_2024_cleaned
plot_2024 <- ggplot(missing_2024, aes(x = reorder(variable, -missing_percentage), y = missing_percentage)) +
  geom_bar(stat = "identity", fill = "red") +
  coord_flip() +
  labs(title = "Percentage of Missing Values in data_2024_cleaned", x = "Variables", y = "Missing Percentage") +
  theme_minimal()

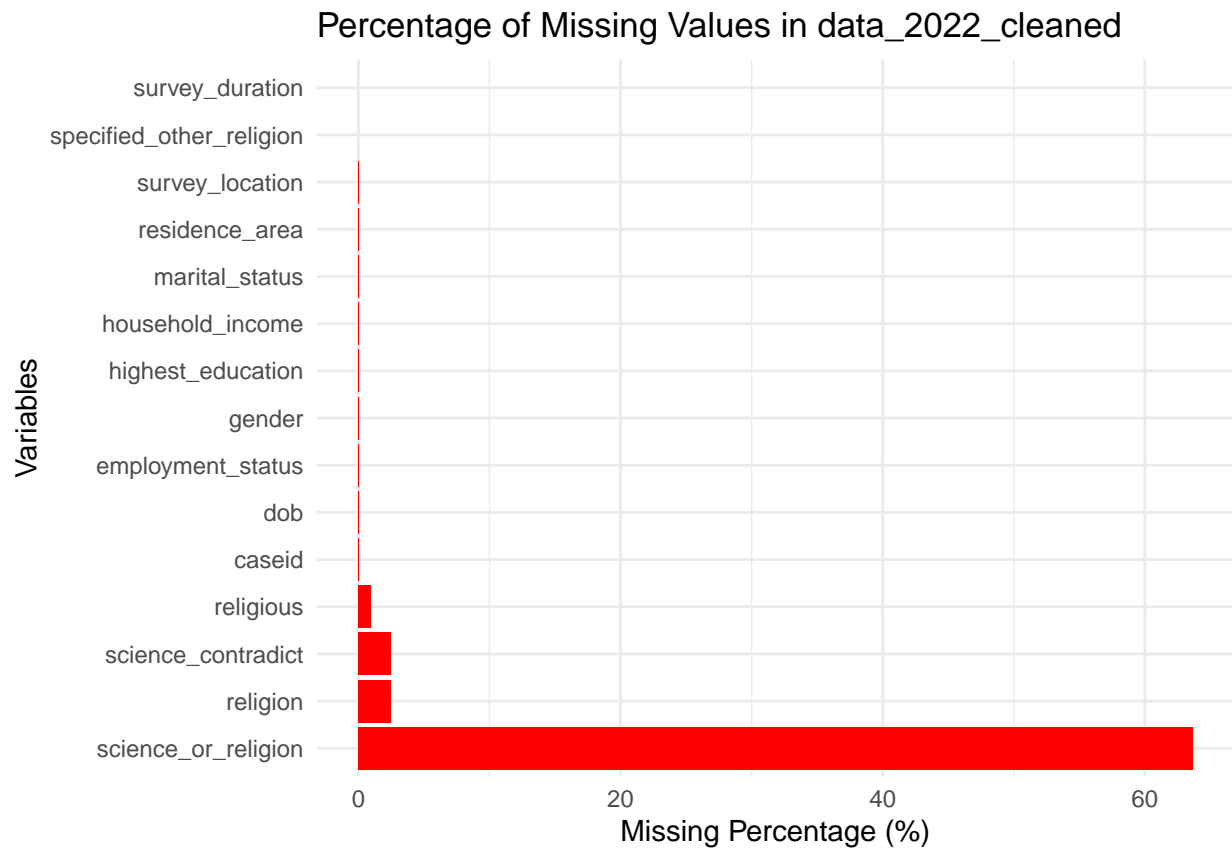
# Display the plots
plot_2022

```

```

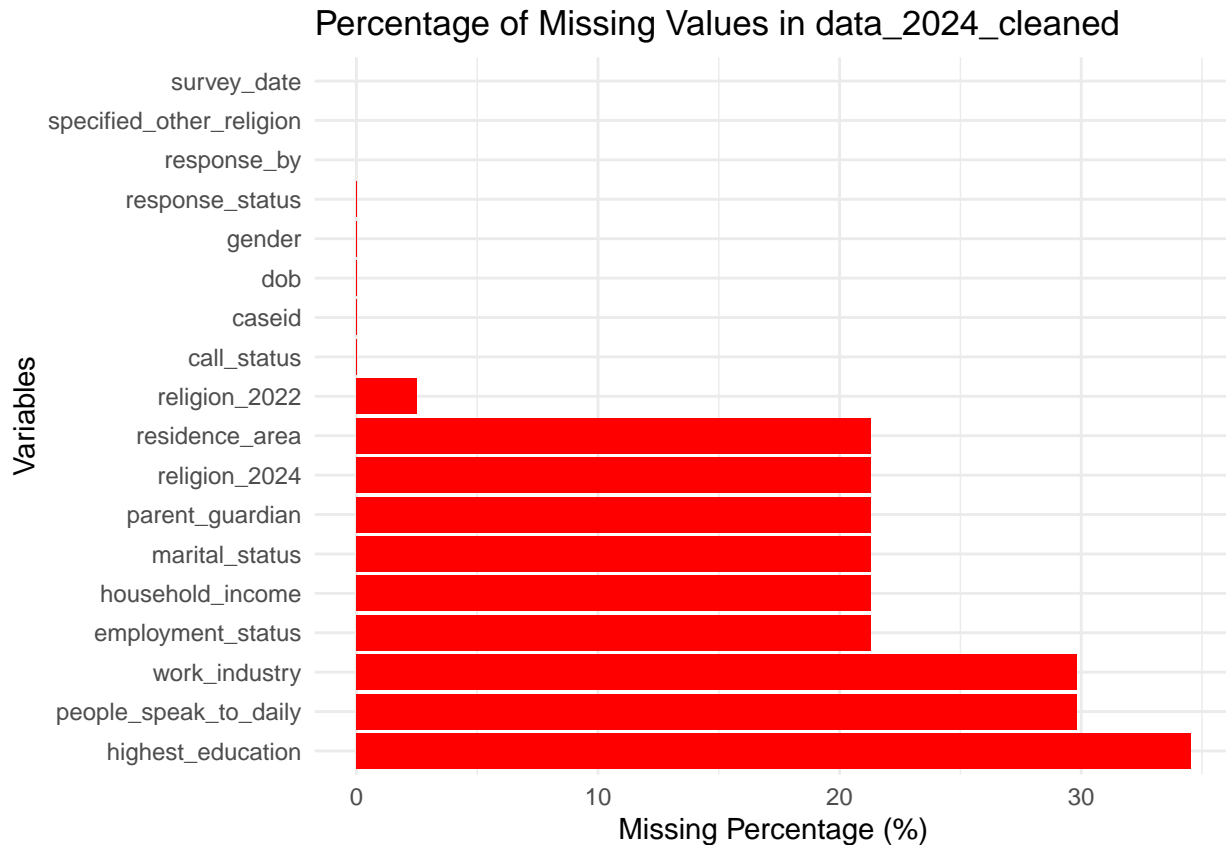
## Warning: Removed 2 rows containing missing values or values outside the scale range
## (`geom_bar()`).

```



plot_2024

```
## Warning: Removed 3 rows containing missing values or values outside the scale range
## (`geom_bar()`).
```



```
# Merge the datasets by caseid and create new variables indicating changes between 2022 and 2024
merged_data <- full_join(data_2022_cleaned, data_2024_cleaned, by = "caseid", suffix = c("_2022", "_2024"))
merged_data <- merged_data %>%
  mutate(lost = if_else(is.na(response_status) | response_status != "Answered the phone, correct response", 1, 0))
merged_data <- merged_data %>%
  mutate(
    education_change = if_else(
      is.na(highest_education_2022) | is.na(highest_education_2024) |
      highest_education_2022 == "Missing" | highest_education_2024 == "Missing",
      3, # Set as 3 when missing in either year
      if_else(highest_education_2022 != highest_education_2024, 1, 0)
    ),
    employment_change = if_else(
      is.na(employment_status_2022) | is.na(employment_status_2024) |
      employment_status_2022 == "Missing" | employment_status_2024 == "Missing",
      3, # Set as 3 when missing in either year
      if_else(employment_status_2022 != employment_status_2024, 1, 0)
    ),
    income_change = if_else(
      is.na(household_income_2022) | is.na(household_income_2024) |
      household_income_2022 == "Missing" | household_income_2024 == "Missing",
      3, # Set as 3 when missing in either year
      if_else(household_income_2022 != household_income_2024, 1, 0)
    ),
    residence_change = if_else(

```

```

    is.na(residence_area_2022) | is.na(residence_area_2024) |
    residence_area_2022 == "Missing" | residence_area_2024 == "Missing",
    3, # Set as 3 when missing in either year
    if_else(residence_area_2022 != residence_area_2024, 1, 0)
  ),

  religion_change = if_else(
    is.na(religion_2022) | is.na(religion_2024) |
    religion_2022 == "Missing" | religion_2024 == "Missing",
    3, # Set as 3 when missing in either year
    if_else(religion_2022 != religion_2024, 1, 0)
  ),

  residence_area_change = if_else(
    is.na(residence_area_2022) | is.na(residence_area_2024) |
    residence_area_2022 == "Missing" | residence_area_2024 == "Missing",
    3, # Set as 3 when missing in either year
    if_else(residence_area_2022 != residence_area_2024, 1, 0)
  )
) %>%
select(
  caseid,
  dob_2022, gender_2022,
  highest_education_2022, highest_education_2024,
  marital_status_2022, marital_status_2024,
  employment_status_2022, employment_status_2024,
  household_income_2022, household_income_2024,
  residence_area_2022, residence_area_2024, residence_area_change,
  religion_2022, religion_2024,
  specified_other_religion_2022,
  response_status, response_by,
  parent_guardian, science_or_religion,
  lost, religious,
  education_change, employment_change, income_change, residence_change, religion_change
)

# View the first few rows to verify the new order
head(merged_data)

```

```

## # A tibble: 6 x 28
##   caseid dob_2022   gender_2022 highest_education_2022 highest_education_2024
##   <chr>  <chr>      <chr>          <chr>                <chr>
## 1 1012   1993-07-04 Male          Secondary            Missing
## 2 1054   1992-02-04 Female         Primary              Missing
## 3 1182   1984-08-17 Female         Higher               Missing
## 4 1220   1992-06-23 Male          Higher               Missing
## 5 1223   1975-01-01 Female         Secondary            Missing
## 6 1255   1982-09-23 Female         Higher               Missing
## # i 23 more variables: marital_status_2022 <chr>, marital_status_2024 <chr>,
## #   employment_status_2022 <chr>, employment_status_2024 <chr>,
## #   household_income_2022 <chr>, household_income_2024 <chr>,
## #   residence_area_2022 <chr>, residence_area_2024 <chr>,
## #   residence_area_change <dbl>, religion_2022 <chr>, religion_2024 <chr>,

```

```
## # specified_other_religion_2022 <chr>, response_status <chr>,
## # response_by <chr>, parent_guardian <chr>, science_or_religion <chr>, ...
```

```
# Summarize the percentages of each change status (0, 1, 3) for each variable
```

```
change_percentages <- merged_data %>%
```

```
  summarize(
```

```
    education_change_0 = mean(education_change == 0, na.rm = TRUE) * 100, # No change
```

```
    education_change_1 = mean(education_change == 1, na.rm = TRUE) * 100, # Changed
```

```
    education_change_3 = mean(education_change == 3, na.rm = TRUE) * 100, # Unknown
```

```
    employment_change_0 = mean(employment_change == 0, na.rm = TRUE) * 100,
```

```
    employment_change_1 = mean(employment_change == 1, na.rm = TRUE) * 100,
```

```
    employment_change_3 = mean(employment_change == 3, na.rm = TRUE) * 100,
```

```
    income_change_0 = mean(income_change == 0, na.rm = TRUE) * 100,
```

```
    income_change_1 = mean(income_change == 1, na.rm = TRUE) * 100,
```

```
    income_change_3 = mean(income_change == 3, na.rm = TRUE) * 100,
```

```
    residence_change_0 = mean(residence_change == 0, na.rm = TRUE) * 100,
```

```
    residence_change_1 = mean(residence_change == 1, na.rm = TRUE) * 100,
```

```
    residence_change_3 = mean(residence_change == 3, na.rm = TRUE) * 100,
```

```
    religion_change_0 = mean(religion_change == 0, na.rm = TRUE) * 100,
```

```
    religion_change_1 = mean(religion_change == 1, na.rm = TRUE) * 100,
```

```
    religion_change_3 = mean(religion_change == 3, na.rm = TRUE) * 100,
```

```
    residence_area_change_0 = mean(residence_area_change == 0, na.rm = TRUE) * 100, # No change in res
```

```
    residence_area_change_1 = mean(residence_area_change == 1, na.rm = TRUE) * 100, # Changed residence
```

```
    residence_area_change_3 = mean(residence_area_change == 3, na.rm = TRUE) * 100 # Unknown/missing
```

```
)
```

```
change_percentages
```

```
## # A tibble: 1 x 18
```

```
##   education_change_0 education_change_1 education_change_3 employment_change_0
```

```
##           <dbl>           <dbl>           <dbl>           <dbl>
```

```
## 1           47.0           18.5           34.5           43.3
```

```
## # i 14 more variables: employment_change_1 <dbl>, employment_change_3 <dbl>,
```

```
## #   income_change_0 <dbl>, income_change_1 <dbl>, income_change_3 <dbl>,
```

```
## #   residence_change_0 <dbl>, residence_change_1 <dbl>,
```

```
## #   residence_change_3 <dbl>, religion_change_0 <dbl>, religion_change_1 <dbl>,
```

```
## #   religion_change_3 <dbl>, residence_area_change_0 <dbl>,
```

```
## #   residence_area_change_1 <dbl>, residence_area_change_3 <dbl>
```

```
dfSummary(merged_data) %>% view()
```

```
## Switching method to 'browser'
```

```
## Output file written: C:\Users\ghlas\AppData\Local\Temp\RtmpGstDKA\file9260515c466d.html
```

```

# Prepare data for pie charts
education_data <- merged_data %>%
  count(education_change) %>%
  mutate(percentage = n / sum(n) * 100)

employment_data <- merged_data %>%
  count(employment_change) %>%
  mutate(percentage = n / sum(n) * 100)

income_data <- merged_data %>%
  count(income_change) %>%
  mutate(percentage = n / sum(n) * 100)

residence_data <- merged_data %>%
  count(residence_change) %>%
  mutate(percentage = n / sum(n) * 100)

religion_data <- merged_data %>%
  count(religion_change) %>%
  mutate(percentage = n / sum(n) * 100)

residence_area_data <- merged_data %>%
  count(residence_area_change) %>%
  mutate(percentage = n / sum(n) * 100)

# Create pie charts for each change status
education_pie <- ggplot(education_data, aes(x = "", y = percentage, fill = factor(education_change))) +
  geom_bar(stat = "identity", width = 1) +
  coord_polar("y", start = 0) +
  labs(title = "Education Change Status", fill = "Status", y = "", x = "") +
  theme_minimal() +
  theme(axis.text.x = element_blank()) +
  scale_fill_manual(values = c("green", "orange", "red"),
                    labels = c("No Change", "Changed", "Missing"))

employment_pie <- ggplot(employment_data, aes(x = "", y = percentage, fill = factor(employment_change))) +
  geom_bar(stat = "identity", width = 1) +
  coord_polar("y", start = 0) +
  labs(title = "Employment Change Status", fill = "Status", y = "", x = "") +
  theme_minimal() +
  theme(axis.text.x = element_blank()) +
  scale_fill_manual(values = c("green", "orange", "red"),
                    labels = c("No Change", "Changed", "Missing"))

income_pie <- ggplot(income_data, aes(x = "", y = percentage, fill = factor(income_change))) +
  geom_bar(stat = "identity", width = 1) +
  coord_polar("y", start = 0) +
  labs(title = "Income Change Status", fill = "Status", y = "", x = "") +
  theme_minimal() +
  theme(axis.text.x = element_blank()) +
  scale_fill_manual(values = c("green", "orange", "red"),
                    labels = c("No Change", "Changed", "Missing"))

```

```

residence_pie <- ggplot(residence_data, aes(x = "", y = percentage, fill = factor(residence_change))) +
  geom_bar(stat = "identity", width = 1) +
  coord_polar("y", start = 0) +
  labs(title = "Residence Change Status", fill = "Status", y = "", x = "") +
  theme_minimal() +
  theme(axis.text.x = element_blank()) +
  scale_fill_manual(values = c("green", "orange", "red"),
                    labels = c("No Change", "Changed", "Missing"))

religion_pie <- ggplot(religion_data, aes(x = "", y = percentage, fill = factor(religion_change))) +
  geom_bar(stat = "identity", width = 1) +
  coord_polar("y", start = 0) +
  labs(title = "Religion Change Status", fill = "Status", y = "", x = "") +
  theme_minimal() +
  theme(axis.text.x = element_blank()) +
  scale_fill_manual(values = c("green", "orange", "red"),
                    labels = c("No Change", "Changed", "Missing"))

residence_area_pie <- ggplot(residence_area_data, aes(x = "", y = percentage, fill = factor(residence_a
  geom_bar(stat = "identity", width = 1) +
  coord_polar("y", start = 0) +
  labs(title = "Residence Area Change Status", fill = "Status", y = "", x = "") +
  theme_minimal() +
  theme(axis.text.x = element_blank()) +
  scale_fill_manual(values = c("green", "orange", "red"),
                    labels = c("No Change", "Changed", "Missing"))

# Arrange the pie charts in a 2 x 3 layout
grid.arrange(education_pie, employment_pie, income_pie, residence_pie, religion_pie, residence_area_pie

```

Education Change Status Employment Change Status Income Change Status



■ No Change
■ Changed
■ Missing



■ No Change
■ Changed
■ Missing



■ No Change
■ Changed
■ Missing

Residence Change Status Religion Change Status Residence Area Change Status



■ No Change
■ Changed
■ Missing



■ No Change
■ Changed
■ Missing



■ No Change
■ Changed
■ Missing

```

# Split data into lost and followed groups
lost_data <- merged_data %>% filter(last == 1)
followed_data <- merged_data %>% filter(last == 0)

```

```

# Function to prepare data for pie chart
prepare_pie_data <- function(data, variable) {
  data %>%
    count({{ variable }}) %>%
    mutate(percentage = n / sum(n) * 100)
}

# Function to create pie chart
create_pie_chart <- function(pie_data, title, variable_name) {
  ggplot(pie_data, aes(x = "", y = percentage, fill = factor({{ variable_name }}))) +
    geom_bar(stat = "identity", width = 1) +
    coord_polar("y", start = 0) +
    labs(title = title, fill = "Status", y = "", x = "") +
    theme_minimal() +
    theme(axis.text.x = element_blank()) +
    scale_fill_manual(values = c("green", "orange", "red"),
                      labels = c("No Change", "Changed", "Missing"))
}

# Prepare data for pie charts for both groups
# For Lost Group
education_lost <- prepare_pie_data(lost_data, education_change)
employment_lost <- prepare_pie_data(lost_data, employment_change)
income_lost <- prepare_pie_data(lost_data, income_change)
residence_lost <- prepare_pie_data(lost_data, residence_change)
religion_lost <- prepare_pie_data(lost_data, religion_change)
residence_area_lost <- prepare_pie_data(lost_data, residence_area_change)

# For Followed Group
education_followed <- prepare_pie_data(followed_data, education_change)
employment_followed <- prepare_pie_data(followed_data, employment_change)
income_followed <- prepare_pie_data(followed_data, income_change)
residence_followed <- prepare_pie_data(followed_data, residence_change)
religion_followed <- prepare_pie_data(followed_data, religion_change)
residence_area_followed <- prepare_pie_data(followed_data, residence_area_change)

# Create pie charts for lost group
education_pie_lost <- create_pie_chart(education_lost, "Education Change", education_change)
employment_pie_lost <- create_pie_chart(employment_lost, "Employment Change", employment_change)
income_pie_lost <- create_pie_chart(income_lost, "Income Change", income_change)
residence_pie_lost <- create_pie_chart(residence_lost, "Residence Change", residence_change)
religion_pie_lost <- create_pie_chart(religion_lost, "Religion Change", religion_change)
residence_area_pie_lost <- create_pie_chart(residence_area_lost, "Residence Area Change", residence_area_change)

# Create pie charts for followed group
education_pie_followed <- create_pie_chart(education_followed, "Education Change", education_change)
employment_pie_followed <- create_pie_chart(employment_followed, "Employment Change", employment_change)
income_pie_followed <- create_pie_chart(income_followed, "Income Change", income_change)
residence_pie_followed <- create_pie_chart(residence_followed, "Residence Change", residence_change)
religion_pie_followed <- create_pie_chart(religion_followed, "Religion Change", religion_change)
residence_area_pie_followed <- create_pie_chart(residence_area_followed, "Residence Area Change", residence_area_change)

# Arrange the pie charts in two sets (Lost and Followed)

```



```
# Lost group: 2 rows x 3 columns
```

```
grid.arrange(education_pie_lost, employment_pie_lost, income_pie_lost,  
              residence_pie_lost, religion_pie_lost, residence_area_pie_lost,  
              ncol = 3, top = "Lost Group")
```

Lost Group

Education Change



No Change
Changed
Missing

Employment Change



No Change
Changed
Missing

Income Change



No Change
Changed
Missing

Residence Change



No Change
Changed
Missing

Religion Change



No Change
Changed
Missing

Residence Area Change



No Change
Changed
Missing

```
# Followed group: 2 rows x 3 columns
```

```
grid.arrange(education_pie_followed, employment_pie_followed, income_pie_followed,  
              residence_pie_followed, religion_pie_followed, residence_area_pie_followed,  
              ncol = 3, top = "Followed Group")
```

Followed Group

Education Change



No Change
Changed
Missing

Employment Change



No Change
Changed
Missing

Income Change



No Change
Changed
Missing

Residence Change



No Change
Changed
Missing

Religion Change



No Change
Changed
Missing

Residence Area Change



No Change
Changed
Missing

```
#
merged_data$highest_education_2022 <- as.factor(merged_data$highest_education_2022)
merged_data$employment_status_2022 <- as.factor(merged_data$employment_status_2022)
merged_data$household_income_2022 <- as.factor(merged_data$household_income_2022)
merged_data$residence_area_2022 <- as.factor(merged_data$residence_area_2022)
merged_data$gender_2022 <- as.factor(merged_data$gender_2022)
merged_data$marital_status_2022 <- as.factor(merged_data$marital_status_2022)
merged_data$religion_2022 <- as.factor(merged_data$religion_2022)
merged_data$lost <- as.factor(merged_data$lost)
merged_data$science_or_religion <- as.factor(merged_data$science_or_religion)
```

```
#           "Missing"  "Prefer not to answer"
clean_data <- merged_data %>%
  filter(
    !highest_education_2022 %in% c("Missing") &
    !employment_status_2022 %in% c("Missing") &
    !household_income_2022 %in% c("Missing") &
    !residence_area_2022 %in% c("Missing") &
    !gender_2022 %in% c("Missing") &
    !marital_status_2022 %in% c("Missing") &
    !religion_2022 %in% c("Missing")
  )
# specified_other_religion_2022 response_by
clean_data <- clean_data %>%
  select(-specified_other_religion_2022, -response_by)

#
print(dim(clean_data)) #
```

```
## [1] 1370  26
```

```
#
clean_model <- glm(loss ~ highest_education_2022 + employment_status_2022 + household_income_2022 + res
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```
#
summary(clean_model)
```

```
##
## Call:
## glm(formula = loss ~ highest_education_2022 + employment_status_2022 +
##       household_income_2022 + residence_area_2022 + gender_2022 +
##       marital_status_2022 + religion_2022, family = binomial, data = clean_data)
##
## Coefficients:
##                                     Estimate
## (Intercept)                        0.14683
## highest_education_2022No school/Did not complete primary 0.17864
## highest_education_2022Primary      0.13832
## highest_education_2022Secondary    0.25153
## employment_status_2022Employed full-time -0.46860
## employment_status_2022Employed part-time -0.15634
## employment_status_2022Not employed and not looking for work -0.15416
## employment_status_2022Not employed but looking for work -0.31022
## employment_status_2022Prefer not to answer -28.62845
## employment_status_2022Self-employed -0.19386
## household_income_2022Allowed me to save just a little -0.13369
## household_income_2022Only just met my expenses -0.36623
## household_income_2022Prefer not to answer -0.90195
## household_income_2022Was not sufficient, so needed to use savings to meet expenses -0.18930
## household_income_2022Was really not sufficient, so needed to borrow to meet expenses -0.72224
## residence_area_2022Trading Center (town) -0.12989
## residence_area_2022Village (rural) -0.22297
## gender_2022Male -0.34320
## marital_status_2022Divorced/Separated -1.29711
## marital_status_2022Married -1.08374
## marital_status_2022Prefer not to answer 14.65645
## marital_status_2022Single -0.84313
## marital_status_2022Widowed -1.11145
## religion_2022Baptist -0.05014
## religion_2022Catholic 0.27565
## religion_2022Muslim 0.82240
## religion_2022Other -0.28737
## religion_2022Other Christian 0.14829
## religion_2022Prefer not to answer -0.83134
##                                     Std. Error
## (Intercept)                        1.11207
## highest_education_2022No school/Did not complete primary 0.36247
## highest_education_2022Primary      0.20526
## highest_education_2022Secondary    0.18512
## employment_status_2022Employed full-time 0.27555
## employment_status_2022Employed part-time 0.43657
## employment_status_2022Not employed and not looking for work 0.34606
```

## employment_status_2022Not employed but looking for work	0.29186
## employment_status_2022Prefer not to answer	868.34868
## employment_status_2022Self-employed	0.23410
## household_income_2022Allowed me to save just a little	0.44519
## household_income_2022Only just met my expenses	0.38772
## household_income_2022Prefer not to answer	1.13526
## household_income_2022Was not sufficient, so needed to use savings to meet expenses	0.41397
## household_income_2022Was really not sufficient, so needed to borrow to meet expenses	0.39219
## residence_area_2022Trading Center (town)	0.19705
## residence_area_2022Village (rural)	0.19138
## gender_2022Male	0.15658
## marital_status_2022Divorced/Separated	1.03949
## marital_status_2022Married	0.96698
## marital_status_2022Prefer not to answer	634.47620
## marital_status_2022Single	0.97936
## marital_status_2022Widowed	1.04607
## religion_2022Baptist	0.80711
## religion_2022Catholic	0.27974
## religion_2022Muslim	0.34868
## religion_2022Other	0.80681
## religion_2022Other Christian	0.25909
## religion_2022Prefer not to answer	1187.49657
##	z value
## (Intercept)	0.132
## highest_education_2022No school/Did not complete primary	0.493
## highest_education_2022Primary	0.674
## highest_education_2022Secondary	1.359
## employment_status_2022Employed full-time	-1.701
## employment_status_2022Employed part-time	-0.358
## employment_status_2022Not employed and not looking for work	-0.445
## employment_status_2022Not employed but looking for work	-1.063
## employment_status_2022Prefer not to answer	-0.033
## employment_status_2022Self-employed	-0.828
## household_income_2022Allowed me to save just a little	-0.300
## household_income_2022Only just met my expenses	-0.945
## household_income_2022Prefer not to answer	-0.794
## household_income_2022Was not sufficient, so needed to use savings to meet expenses	-0.457
## household_income_2022Was really not sufficient, so needed to borrow to meet expenses	-1.842
## residence_area_2022Trading Center (town)	-0.659
## residence_area_2022Village (rural)	-1.165
## gender_2022Male	-2.192
## marital_status_2022Divorced/Separated	-1.248
## marital_status_2022Married	-1.121
## marital_status_2022Prefer not to answer	0.023
## marital_status_2022Single	-0.861
## marital_status_2022Widowed	-1.062
## religion_2022Baptist	-0.062
## religion_2022Catholic	0.985
## religion_2022Muslim	2.359
## religion_2022Other	-0.356
## religion_2022Other Christian	0.572
## religion_2022Prefer not to answer	-0.001
##	Pr(> z)
## (Intercept)	0.8950

## highest_education_2022No school/Did not complete primary	0.6221
## highest_education_2022Primary	0.5004
## highest_education_2022Secondary	0.1742
## employment_status_2022Employed full-time	0.0890
## employment_status_2022Employed part-time	0.7203
## employment_status_2022Not employed and not looking for work	0.6560
## employment_status_2022Not employed but looking for work	0.2878
## employment_status_2022Prefer not to answer	0.9737
## employment_status_2022Self-employed	0.4076
## household_income_2022Allowed me to save just a little	0.7639
## household_income_2022Only just met my expenses	0.3449
## household_income_2022Prefer not to answer	0.4269
## household_income_2022Was not sufficient, so needed to use savings to meet expenses	0.6475
## household_income_2022Was really not sufficient, so needed to borrow to meet expenses	0.0655
## residence_area_2022Trading Center (town)	0.5098
## residence_area_2022Village (rural)	0.2440
## gender_2022Male	0.0284
## marital_status_2022Divorced/Separated	0.2121
## marital_status_2022Married	0.2624
## marital_status_2022Prefer not to answer	0.9816
## marital_status_2022Single	0.3893
## marital_status_2022Widowed	0.2880
## religion_2022Baptist	0.9505
## religion_2022Catholic	0.3244
## religion_2022Muslim	0.0183
## religion_2022Other	0.7217
## religion_2022Other Christian	0.5671
## religion_2022Prefer not to answer	0.9994
##	
## (Intercept)	
## highest_education_2022No school/Did not complete primary	
## highest_education_2022Primary	
## highest_education_2022Secondary	
## employment_status_2022Employed full-time	
## employment_status_2022Employed part-time	
## employment_status_2022Not employed and not looking for work	
## employment_status_2022Not employed but looking for work	
## employment_status_2022Prefer not to answer	
## employment_status_2022Self-employed	
## household_income_2022Allowed me to save just a little	
## household_income_2022Only just met my expenses	
## household_income_2022Prefer not to answer	
## household_income_2022Was not sufficient, so needed to use savings to meet expenses	
## household_income_2022Was really not sufficient, so needed to borrow to meet expenses	
## residence_area_2022Trading Center (town)	
## residence_area_2022Village (rural)	
## gender_2022Male	*
## marital_status_2022Divorced/Separated	
## marital_status_2022Married	
## marital_status_2022Prefer not to answer	
## marital_status_2022Single	
## marital_status_2022Widowed	
## religion_2022Baptist	
## religion_2022Catholic	

```

## religion_2022Muslim
## religion_2022Other
## religion_2022Other Christian
## religion_2022Prefer not to answer
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##    Null deviance: 1274.5  on 1369  degrees of freedom
## Residual deviance: 1234.4  on 1341  degrees of freedom
## AIC: 1292.4
##
## Number of Fisher Scoring iterations: 14

```

```

#
simplified_model <- glm(loss ~ employment_status_2022 + gender_2022 + religion_2022,
                        data = clean_data, family = binomial)
#
summary(simplified_model)

```

```

##
## Call:
## glm(formula = loss ~ employment_status_2022 + gender_2022 + religion_2022,
##      family = binomial, data = clean_data)
##
## Coefficients:
##
## (Intercept)
## employment_status_2022Employed full-time
## employment_status_2022Employed part-time
## employment_status_2022Not employed and not looking for work
## employment_status_2022Not employed but looking for work
## employment_status_2022Prefer not to answer
## employment_status_2022Self-employed
## gender_2022Male
## religion_2022Baptist
## religion_2022Catholic
## religion_2022Muslim
## religion_2022Other
## religion_2022Other Christian
## religion_2022Prefer not to answer
##
## (Intercept)
## employment_status_2022Employed full-time
## employment_status_2022Employed part-time
## employment_status_2022Not employed and not looking for work
## employment_status_2022Not employed but looking for work
## employment_status_2022Prefer not to answer
## employment_status_2022Self-employed
## gender_2022Male
## religion_2022Baptist
## religion_2022Catholic
## religion_2022Muslim

```

	Estimate	Std. Error	z value
(Intercept)	-1.35863	0.31070	-4.373
employment_status_2022Employed full-time	-0.44703	0.25369	-1.762
employment_status_2022Employed part-time	-0.20938	0.42179	-0.496
employment_status_2022Not employed and not looking for work	-0.16233	0.34121	-0.476
employment_status_2022Not employed but looking for work	-0.28798	0.28619	-1.006
employment_status_2022Prefer not to answer	-13.26068	440.28389	-0.030
employment_status_2022Self-employed	-0.17398	0.22770	-0.764
gender_2022Male	-0.36444	0.14987	-2.432
religion_2022Baptist	-0.12530	0.80035	-0.157
religion_2022Catholic	0.26719	0.27743	0.963
religion_2022Muslim	0.84886	0.34042	2.494
religion_2022Other	-0.23183		
religion_2022Other Christian	0.13760		
religion_2022Prefer not to answer	0.05324		

```
## religion_2022Other                0.79550 -0.291
## religion_2022Other Christian      0.25668  0.536
## religion_2022Prefer not to answer 763.85068  0.000
##                                Pr(>|z|)
## (Intercept)                    1.23e-05 ***
## employment_status_2022Employed full-time    0.0781 .
## employment_status_2022Employed part-time    0.6196
## employment_status_2022Not employed and not looking for work 0.6343
## employment_status_2022Not employed but looking for work    0.3143
## employment_status_2022Prefer not to answer    0.9760
## employment_status_2022Self-employed          0.4448
## gender_2022Male                          0.0150 *
## religion_2022Baptist                     0.8756
## religion_2022Catholic                    0.3355
## religion_2022Muslim                      0.0126 *
## religion_2022Other                      0.7707
## religion_2022Other Christian              0.5919
## religion_2022Prefer not to answer          0.9999
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##    Null deviance: 1274.5  on 1369  degrees of freedom
## Residual deviance: 1254.5  on 1356  degrees of freedom
## AIC: 1282.5
##
## Number of Fisher Scoring iterations: 13
```

```
chi_square_test <- anova(simplified_model, clean_model, test = "Chisq")
print(chi_square_test)
```

```
## Analysis of Deviance Table
##
## Model 1: lost ~ employment_status_2022 + gender_2022 + religion_2022
## Model 2: lost ~ highest_education_2022 + employment_status_2022 + household_income_2022 +
##   residence_area_2022 + gender_2022 + marital_status_2022 +
##   religion_2022
##   Resid. Df Resid. Dev Df Deviance Pr(>Chi)
## 1      1356      1254.5
## 2      1341      1234.4 15    20.08  0.1689
```

```
predicted_probs <- predict(simplified_model, type = "response")
predicted_class <- ifelse(predicted_probs > 0.5, 1, 0)

#
confusion_matrix <- table(Predicted = predicted_class, Actual = clean_data$lost)
print("Confusion Matrix:")
```

```
## [1] "Confusion Matrix:"
```

```
print(confusion_matrix)
```

```
##           Actual
## Predicted    0    1
##           0 1129  241
```

```
#   ROC   AUC
library(pROC)
```

```
## Type 'citation("pROC")' for a citation.
```

```
##
## Attaching package: 'pROC'
```

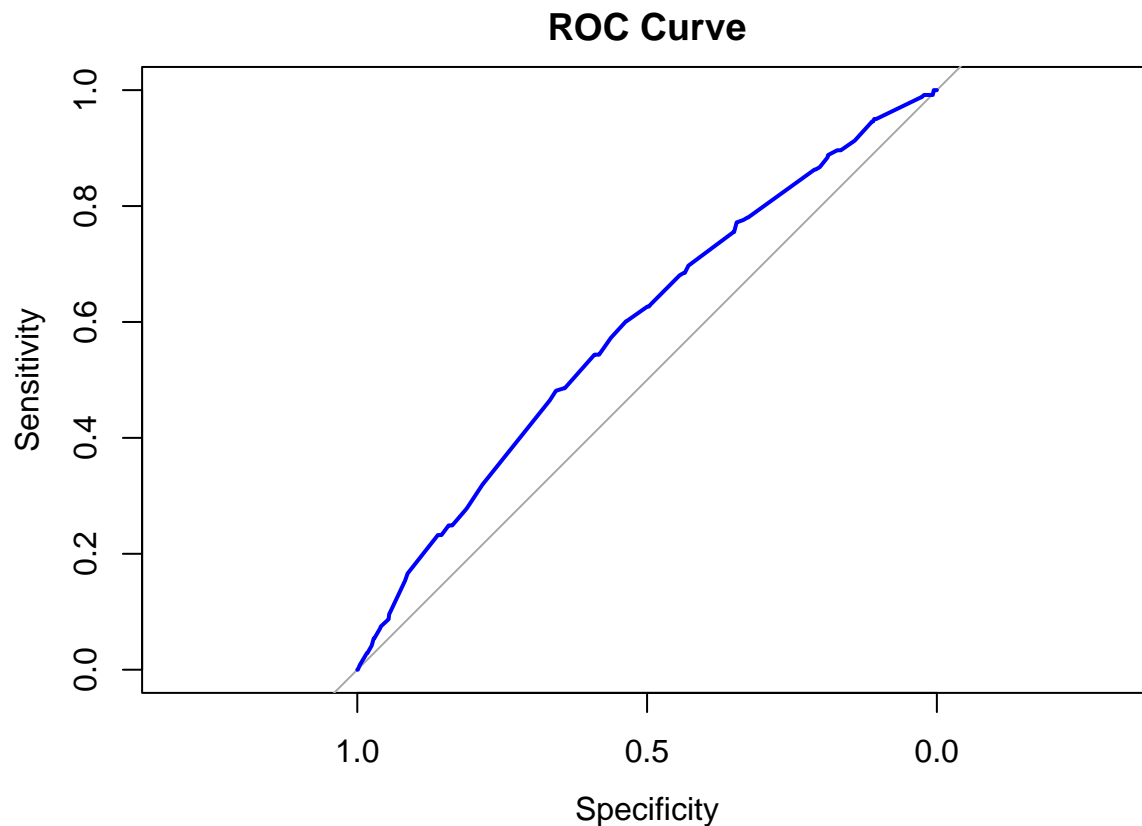
```
## The following objects are masked from 'package:stats':
##
##   cov, smooth, var
```

```
roc_curve <- roc(clean_data$lost, predicted_probs)
```

```
## Setting levels: control = 0, case = 1
```

```
## Setting direction: controls < cases
```

```
#   ROC
plot(roc_curve, main = "ROC Curve", col = "blue", lwd = 2)
```




```
auc_value <- auc(roc_curve)
cat("AUC:", auc_value, "\n")
```

```
## AUC: 0.5909463
```

```
# McFadden's R^2
null_model <- glm(loss ~ 1, data = clean_data, family = binomial) #
r2_mcfadden <- 1 - (logLik(clean_model) / logLik(null_model))
cat("McFadden's R^2:", r2_mcfadden, "\n")
```

```
## McFadden's R^2: 0.03146567
```

```
# dependent variable
library(nnet)
multinom_model <- multinom(loss ~ highest_education_2022 + employment_status_2022 + household_income_2022 +
  residence_area_2022 + gender_2022 + marital_status_2022 + religion_2022, data = clean_data)
```

```
## # weights: 31 (30 variable)
## initial value 949.611637
## iter 10 value 626.110543
## iter 20 value 618.256318
## iter 30 value 617.283672
## iter 40 value 617.188491
## final value 617.188359
## converged
```

```
summary(multinom_model)
```

```
## Warning in sqrt(diag(vc)): NaNs produced
```

```
## Call:
```

```
## multinom(formula = loss ~ highest_education_2022 + employment_status_2022 +
## household_income_2022 + residence_area_2022 + gender_2022 +
## marital_status_2022 + religion_2022, data = clean_data)
##
```

```
## Coefficients:
```

	Values
## (Intercept)	0.14742349
## highest_education_2022No school/Did not complete primary	0.17863717
## highest_education_2022Primary	0.13830897
## highest_education_2022Secondary	0.25152577
## employment_status_2022Employed full-time	-0.46865538
## employment_status_2022Employed part-time	-0.15640228
## employment_status_2022Not employed and not looking for work	-0.15418654
## employment_status_2022Not employed but looking for work	-0.31025301
## employment_status_2022Prefer not to answer	-28.30852483
## employment_status_2022Self-employed	-0.19388660
## household_income_2022Allowed me to save just a little	-0.13368377
## household_income_2022Only just met my expenses	-0.36625146
## household_income_2022Prefer not to answer	-0.90209426
## household_income_2022Was not sufficient, so needed to use savings to meet expenses	-0.18930560

```

## household_income_2022Was really not sufficient, so needed to borrow to meet expenses -0.72225588
## residence_area_2022Trading Center (town) -0.12988465
## residence_area_2022Village (rural) -0.22299043
## gender_2022Male -0.34320861
## marital_status_2022Divorced/Separated -1.29763593
## marital_status_2022Married -1.08425834
## marital_status_2022Prefer not to answer 12.90474401
## marital_status_2022Single -0.84365666
## marital_status_2022Widowed -1.11199580
## religion_2022Baptist -0.05016383
## religion_2022Catholic 0.27564002
## religion_2022Missing 0.00000000
## religion_2022Muslim 0.82238523
## religion_2022Other -0.28742941
## religion_2022Other Christian 0.14827778
## religion_2022Prefer not to answer -6.48798801
## Std. Err.
## (Intercept) 1.11203850
## highest_education_2022No school/Did not complete primary 0.36247104
## highest_education_2022Primary 0.20526193
## highest_education_2022Secondary 0.18512010
## employment_status_2022Employed full-time 0.27554931
## employment_status_2022Employed part-time 0.43656848
## employment_status_2022Not employed and not looking for work 0.34606262
## employment_status_2022Not employed but looking for work 0.29186074
## employment_status_2022Prefer not to answer NaN
## employment_status_2022Self-employed 0.23409971
## household_income_2022Allowed me to save just a little 0.44518623
## household_income_2022Only just met my expenses 0.38771809
## household_income_2022Prefer not to answer 1.13530548
## household_income_2022Was not sufficient, so needed to use savings to meet expenses 0.41397104
## household_income_2022Was really not sufficient, so needed to borrow to meet expenses 0.39218638
## residence_area_2022Trading Center (town) 0.19704736
## residence_area_2022Village (rural) 0.19137808
## gender_2022Male 0.15658003
## marital_status_2022Divorced/Separated 1.03945919
## marital_status_2022Married 0.96694511
## marital_status_2022Prefer not to answer 0.00002428
## marital_status_2022Single 0.97932726
## marital_status_2022Widowed 1.04604019
## religion_2022Baptist 0.80711844
## religion_2022Catholic 0.27973636
## religion_2022Missing NaN
## religion_2022Muslim 0.34868337
## religion_2022Other 0.80681282
## religion_2022Other Christian 0.25908972
## religion_2022Prefer not to answer 0.00000000
##
## Residual Deviance: 1234.377
## AIC: 1292.377

```

```

# lost
clean_data$lost <- as.integer(clean_data$lost)

```

```
poisson_model <- glm(loss ~ highest_education_2022 + employment_status_2022 + household_income_2022 +
  residence_area_2022 + gender_2022 + marital_status_2022 + religion_2022,
  data = clean_data, family = poisson)
summary(poisson_model)
```

```
##
## Call:
## glm(formula = loss ~ highest_education_2022 + employment_status_2022 +
##   household_income_2022 + residence_area_2022 + gender_2022 +
##   marital_status_2022 + religion_2022, family = poisson, data = clean_data)
##
## Coefficients:
##                                     Estimate
## (Intercept)                        0.404624
## highest_education_2022No school/Did not complete primary 0.017536
## highest_education_2022Primary      0.013851
## highest_education_2022Secondary    0.028802
## employment_status_2022Employed full-time -0.057891
## employment_status_2022Employed part-time -0.022087
## employment_status_2022Not employed and not looking for work -0.019981
## employment_status_2022Not employed but looking for work -0.039722
## employment_status_2022Prefer not to answer -0.331398
## employment_status_2022Self-employed -0.024142
## household_income_2022Allowed me to save just a little -0.015098
## household_income_2022Only just met my expenses -0.044596
## household_income_2022Prefer not to answer -0.146204
## household_income_2022Was not sufficient, so needed to use savings to meet expenses -0.020368
## household_income_2022Was really not sufficient, so needed to borrow to meet expenses -0.084610
## residence_area_2022Trading Center (town) -0.014970
## residence_area_2022Village (rural) -0.026408
## gender_2022Male -0.041104
## marital_status_2022Divorced/Separated -0.188995
## marital_status_2022Married -0.164314
## marital_status_2022Prefer not to answer 0.204352
## marital_status_2022Single -0.132949
## marital_status_2022Widowed -0.167990
## religion_2022Baptist -0.002116
## religion_2022Catholic 0.032782
## religion_2022Muslim 0.110256
## religion_2022Other -0.032703
## religion_2022Other Christian 0.018042
## religion_2022Prefer not to answer -0.128150
##                                     Std. Error
## (Intercept)                        0.431344
## highest_education_2022No school/Did not complete primary 0.128151
## highest_education_2022Primary      0.070048
## highest_education_2022Secondary    0.063864
## employment_status_2022Employed full-time 0.095577
## employment_status_2022Employed part-time 0.153799
## employment_status_2022Not employed and not looking for work 0.124460
## employment_status_2022Not employed but looking for work 0.104176
## employment_status_2022Prefer not to answer 0.637558
## employment_status_2022Self-employed 0.083958
```

## household_income_2022Allowed me to save just a little	0.163852
## household_income_2022Only just met my expenses	0.142435
## household_income_2022Prefer not to answer	0.356989
## household_income_2022Was not sufficient, so needed to use savings to meet expenses	0.152919
## household_income_2022Was really not sufficient, so needed to borrow to meet expenses	0.142804
## residence_area_2022Trading Center (town)	0.069322
## residence_area_2022Village (rural)	0.066792
## gender_2022Male	0.053472
## marital_status_2022Divorced/Separated	0.405786
## marital_status_2022Married	0.384972
## marital_status_2022Prefer not to answer	0.739394
## marital_status_2022Single	0.389340
## marital_status_2022Widowed	0.410603
## religion_2022Baptist	0.256564
## religion_2022Catholic	0.093980
## religion_2022Muslim	0.126133
## religion_2022Other	0.251828
## religion_2022Other Christian	0.085867
## religion_2022Prefer not to answer	0.914583
##	z value
## (Intercept)	0.938
## highest_education_2022No school/Did not complete primary	0.137
## highest_education_2022Primary	0.198
## highest_education_2022Secondary	0.451
## employment_status_2022Employed full-time	-0.606
## employment_status_2022Employed part-time	-0.144
## employment_status_2022Not employed and not looking for work	-0.161
## employment_status_2022Not employed but looking for work	-0.381
## employment_status_2022Prefer not to answer	-0.520
## employment_status_2022Self-employed	-0.288
## household_income_2022Allowed me to save just a little	-0.092
## household_income_2022Only just met my expenses	-0.313
## household_income_2022Prefer not to answer	-0.410
## household_income_2022Was not sufficient, so needed to use savings to meet expenses	-0.133
## household_income_2022Was really not sufficient, so needed to borrow to meet expenses	-0.592
## residence_area_2022Trading Center (town)	-0.216
## residence_area_2022Village (rural)	-0.395
## gender_2022Male	-0.769
## marital_status_2022Divorced/Separated	-0.466
## marital_status_2022Married	-0.427
## marital_status_2022Prefer not to answer	0.276
## marital_status_2022Single	-0.341
## marital_status_2022Widowed	-0.409
## religion_2022Baptist	-0.008
## religion_2022Catholic	0.349
## religion_2022Muslim	0.874
## religion_2022Other	-0.130
## religion_2022Other Christian	0.210
## religion_2022Prefer not to answer	-0.140
##	Pr(> z)
## (Intercept)	0.348
## highest_education_2022No school/Did not complete primary	0.891
## highest_education_2022Primary	0.843
## highest_education_2022Secondary	0.652

```
## employment_status_2022Employed full-time 0.545
## employment_status_2022Employed part-time 0.886
## employment_status_2022Not employed and not looking for work 0.872
## employment_status_2022Not employed but looking for work 0.703
## employment_status_2022Prefer not to answer 0.603
## employment_status_2022Self-employed 0.774
## household_income_2022Allowed me to save just a little 0.927
## household_income_2022Only just met my expenses 0.754
## household_income_2022Prefer not to answer 0.682
## household_income_2022Was not sufficient, so needed to use savings to meet expenses 0.894
## household_income_2022Was really not sufficient, so needed to borrow to meet expenses 0.554
## residence_area_2022Trading Center (town) 0.829
## residence_area_2022Village (rural) 0.693
## gender_2022Male 0.442
## marital_status_2022Divorced/Separated 0.641
## marital_status_2022Married 0.670
## marital_status_2022Prefer not to answer 0.782
## marital_status_2022Single 0.733
## marital_status_2022Widowed 0.682
## religion_2022Baptist 0.993
## religion_2022Catholic 0.727
## religion_2022Muslim 0.382
## religion_2022Other 0.897
## religion_2022Other Christian 0.834
## religion_2022Prefer not to answer 0.889
##
## (Dispersion parameter for poisson family taken to be 1)
##
## Null deviance: 146.09 on 1369 degrees of freedom
## Residual deviance: 141.35 on 1341 degrees of freedom
## AIC: 3087.3
##
## Number of Fisher Scoring iterations: 4
```

```
# Load necessary libraries
library(dplyr)
library(ggplot2)

# Define the categorical variables for conversion to dummy variables
categorical_vars <- c("household_income_2022", "highest_education_2022", "employment_status_2022",
  "residence_area_2022", "gender_2022", "marital_status_2022", "religion_2022")

# Combine Lost and Followed groups first and add group label
combined_data <- merged_data %>%
  mutate(group = if_else(lost == 1, "Lost", "Followed")) %>%
  select(all_of(categorical_vars), group) %>%
  filter(!if_any(all_of(categorical_vars), ~ . == "Missing"))

# Convert categorical variables to factors
combined_data <- combined_data %>%
  mutate(across(all_of(categorical_vars), as.factor))

# Apply model.matrix to the combined dataset (convert categorical variables to dummy variables)
combined_data_clean <- model.matrix(~ . - 1, data = combined_data) %>%
```

```

as.data.frame()

# Add group column back to the cleaned data
combined_data_clean$group <- combined_data$group

# Remove the group column before running PCA
combined_data_for_pca <- combined_data_clean %>%
  select(-group)

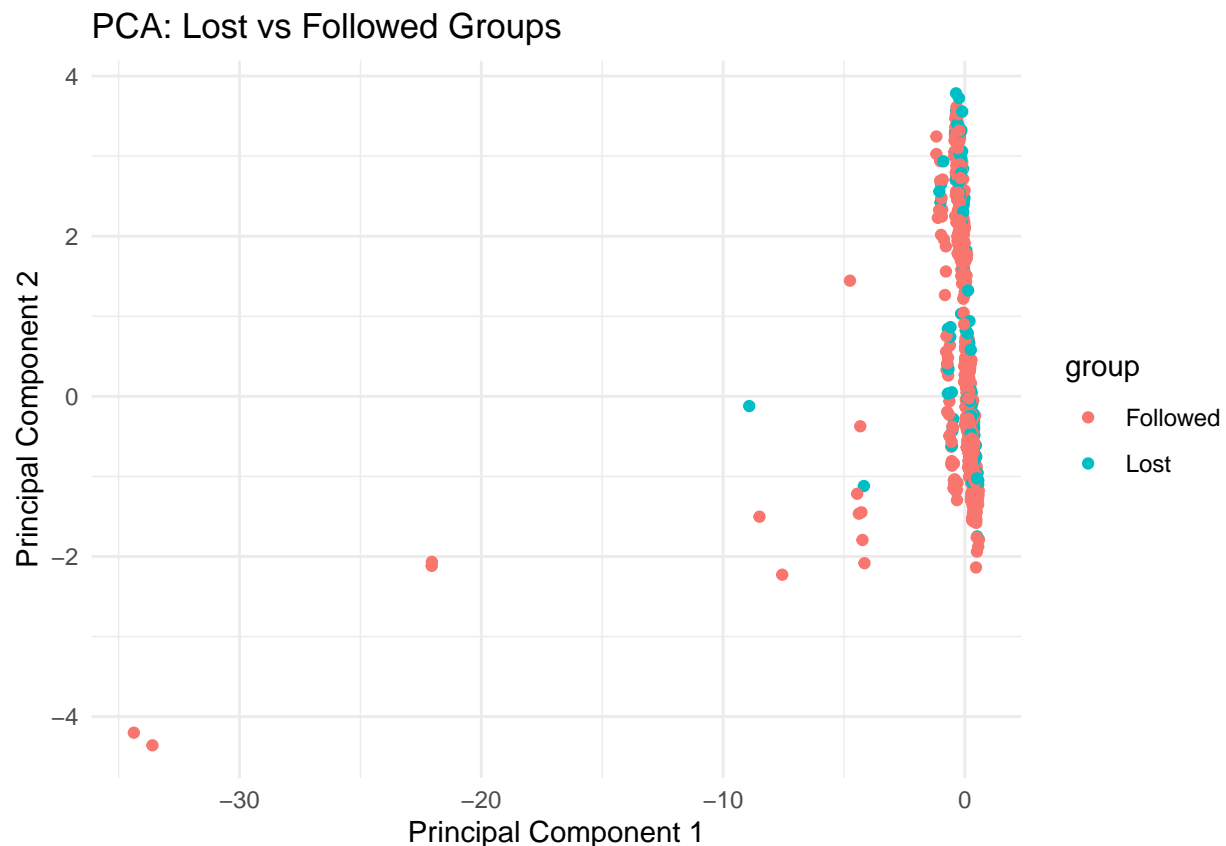
# Remove columns with zero variance (constant columns)
combined_data_for_pca <- combined_data_for_pca[, apply(combined_data_for_pca, 2, var) != 0]

# Perform PCA on the cleaned data, scaling the variables
combined_pca <- prcomp(scale(combined_data_for_pca), center = TRUE, scale. = TRUE)

# Extract the first two principal components and add group labels back
pca_df <- as.data.frame(combined_pca$x[, 1:2])
pca_df$group <- combined_data_clean$group

# Plot the PCA results using ggplot2
ggplot(pca_df, aes(x = PC1, y = PC2, color = group)) +
  geom_point() +
  labs(title = "PCA: Lost vs Followed Groups", x = "Principal Component 1", y = "Principal Component 2") +
  theme_minimal()

```



```

# Initial setup for categorical variables
categorical_vars <- c("household_income_2022", "highest_education_2022", "employment_status_2022",
  "residence_area_2022", "gender_2022", "marital_status_2022", "religion_2022")

# Combine Lost and Followed groups first and add group label
combined_data <- merged_data %>%
  mutate(group = if_else(lost == 1, "Lost", "Followed")) %>%
  select(all_of(categorical_vars), group) %>%
  filter(!if_any(all_of(categorical_vars), ~ . == "Missing"))

# Convert categorical variables to factors
combined_data <- combined_data %>%
  mutate(across(all_of(categorical_vars), as.factor))

# Apply model.matrix to the combined dataset (with consistent dummy variables for both groups)
combined_data_clean <- model.matrix(~ . - 1, data = combined_data) %>%
  as.data.frame()

# Add group column back to the cleaned data
combined_data_clean$group <- combined_data$group

# Remove the group column before running PCA
combined_data_for_pca <- combined_data_clean %>%
  select(-group)

# Identify and remove columns with zero variance
combined_data_for_pca <- combined_data_for_pca[, apply(combined_data_for_pca, 2, var) != 0]

# 1. Standardize the data
combined_data_for_pca_scaled <- scale(combined_data_for_pca)

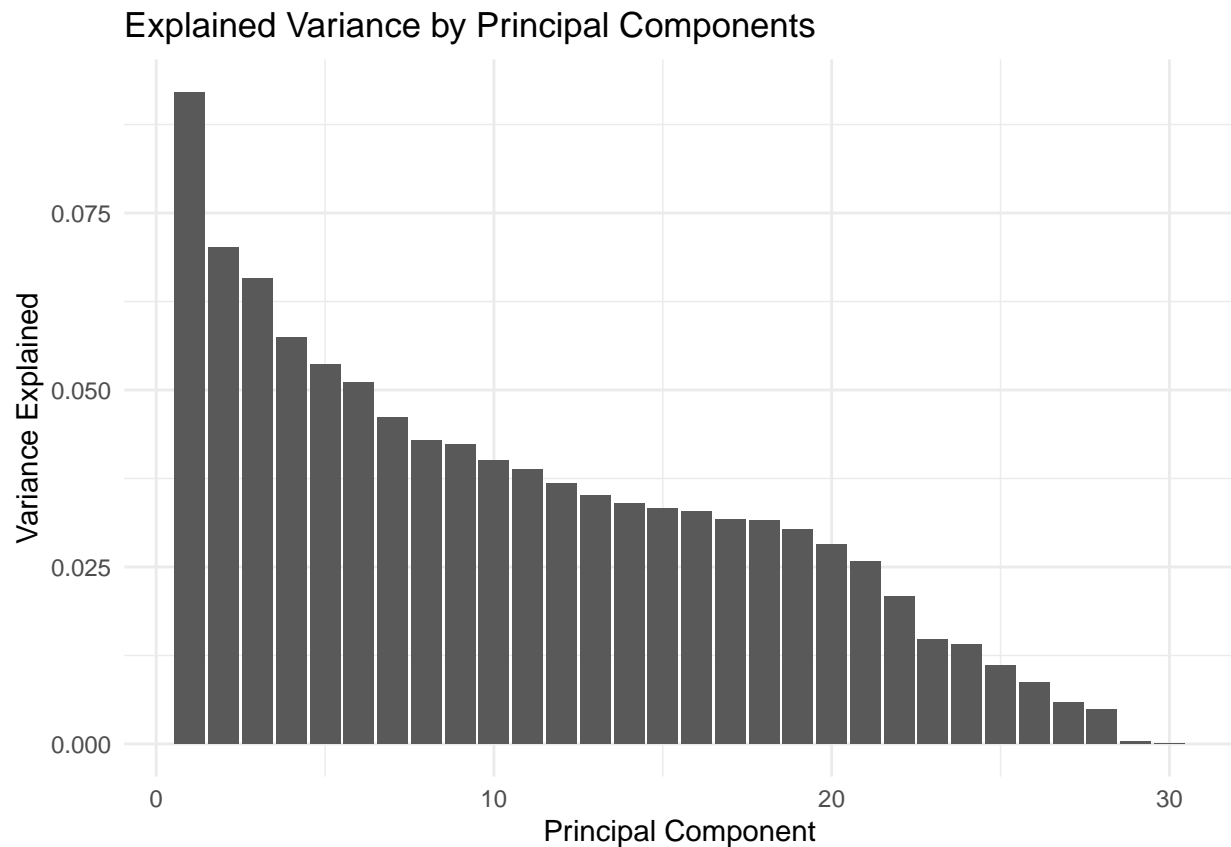
# 2. Perform PCA on the scaled data
combined_pca_scaled <- prcomp(combined_data_for_pca_scaled, center = TRUE, scale. = TRUE)

# 3. Calculate explained variance
explained_variance <- combined_pca_scaled$sdev^2 / sum(combined_pca_scaled$sdev^2)

# 4. Plot the explained variance for each principal component
explained_variance_df <- data.frame(
  PC = seq_along(explained_variance),
  Variance = explained_variance
)

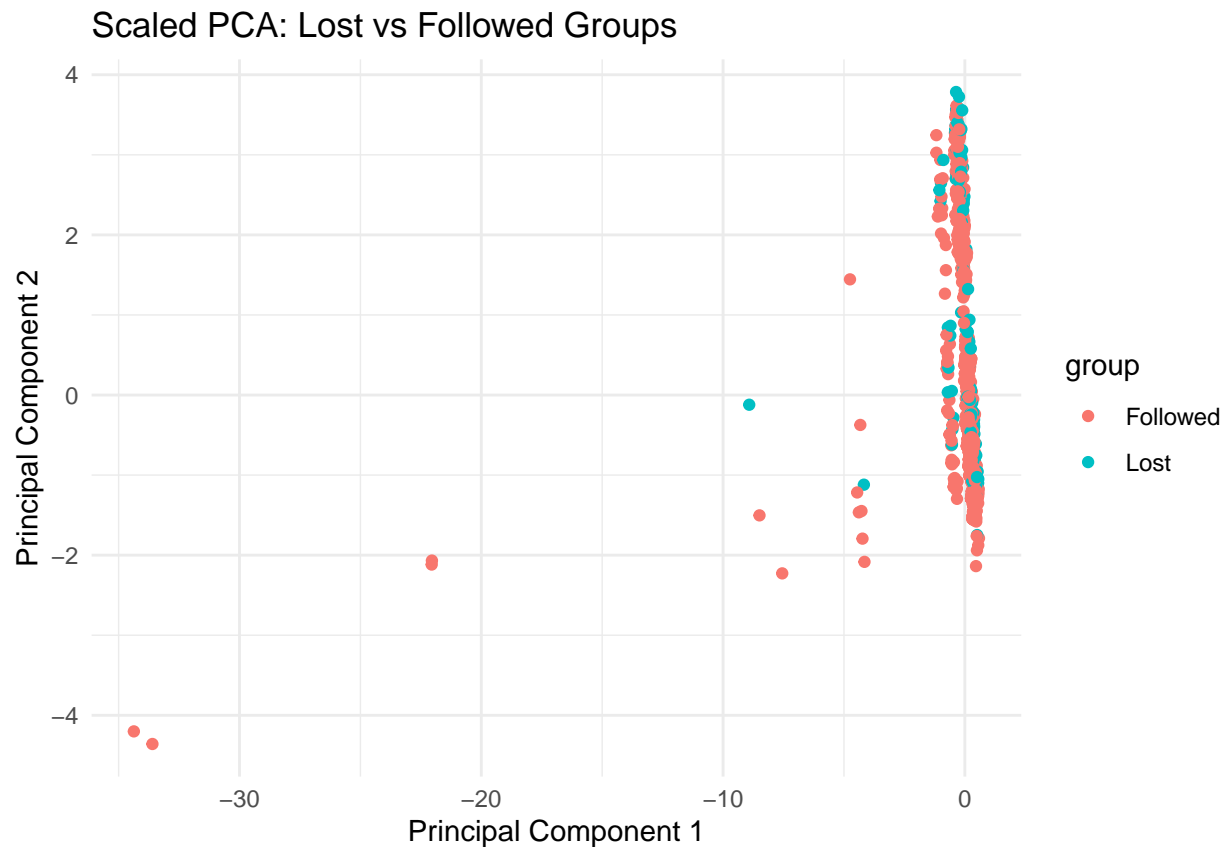
ggplot(explained_variance_df, aes(x = PC, y = Variance)) +
  geom_bar(stat = "identity") +
  labs(title = "Explained Variance by Principal Components", x = "Principal Component", y = "Variance Explained") +
  theme_minimal()

```



```
# 5. Extract the first two principal components and plot PCA
pca_df_scaled <- as.data.frame(combined_pca_scaled$x[, 1:2])
pca_df_scaled$group <- combined_data_clean$group

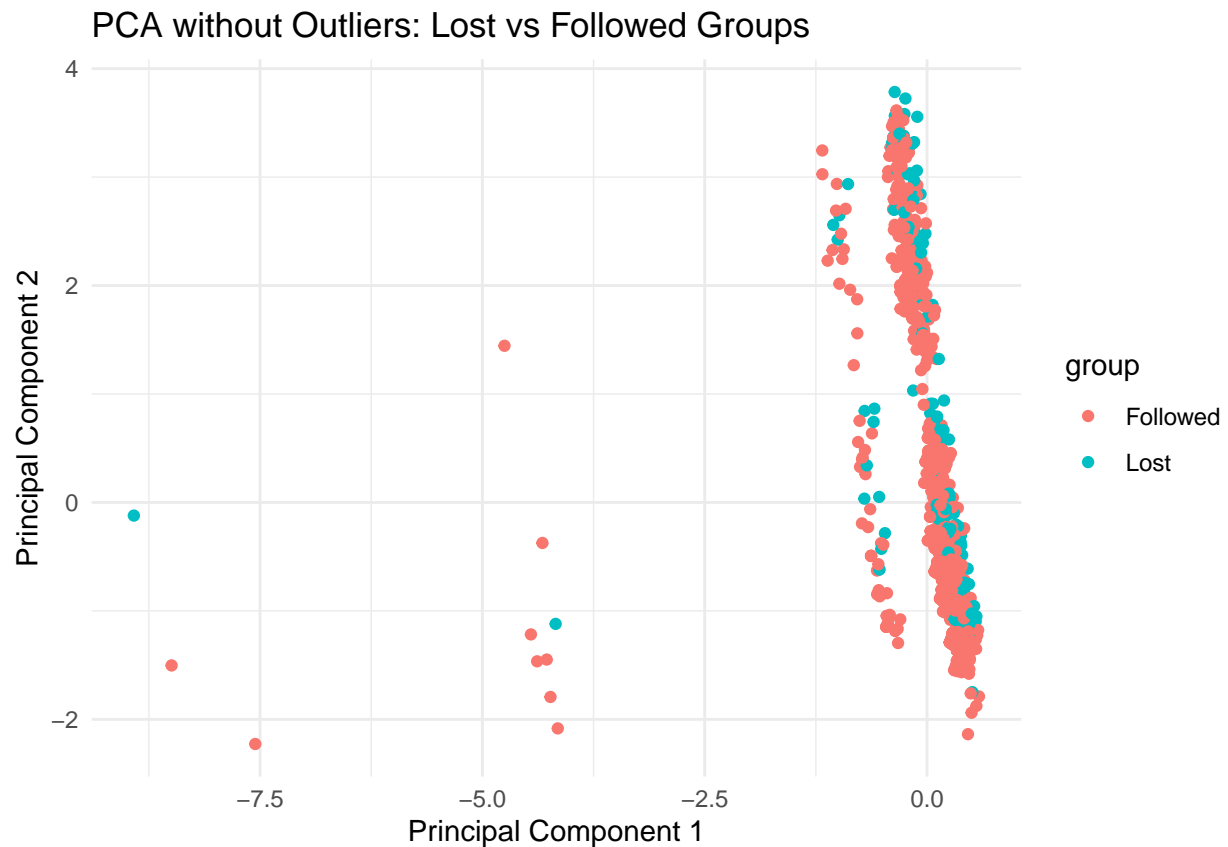
# Plot PCA results
ggplot(pca_df_scaled, aes(x = PC1, y = PC2, color = group)) +
  geom_point() +
  labs(title = "Scaled PCA: Lost vs Followed Groups", x = "Principal Component 1", y = "Principal Component 2") +
  theme_minimal()
```

```
# 6. Identify outliers based on PCA results
outliers <- pca_df_scaled %>%
  filter(PC1 < -10 | PC2 < -10)

# 7. Remove outliers and re-plot PCA without outliers
pca_df_cleaned <- pca_df_scaled %>%
  filter(PC1 > -10 & PC2 > -10) # Assuming -10 is the threshold for outliers

# Re-plot PCA without outliers
ggplot(pca_df_cleaned, aes(x = PC1, y = PC2, color = group)) +
  geom_point() +
  labs(title = "PCA without Outliers: Lost vs Followed Groups", x = "Principal Component 1", y = "Principal Component 2") +
  theme_minimal()
```



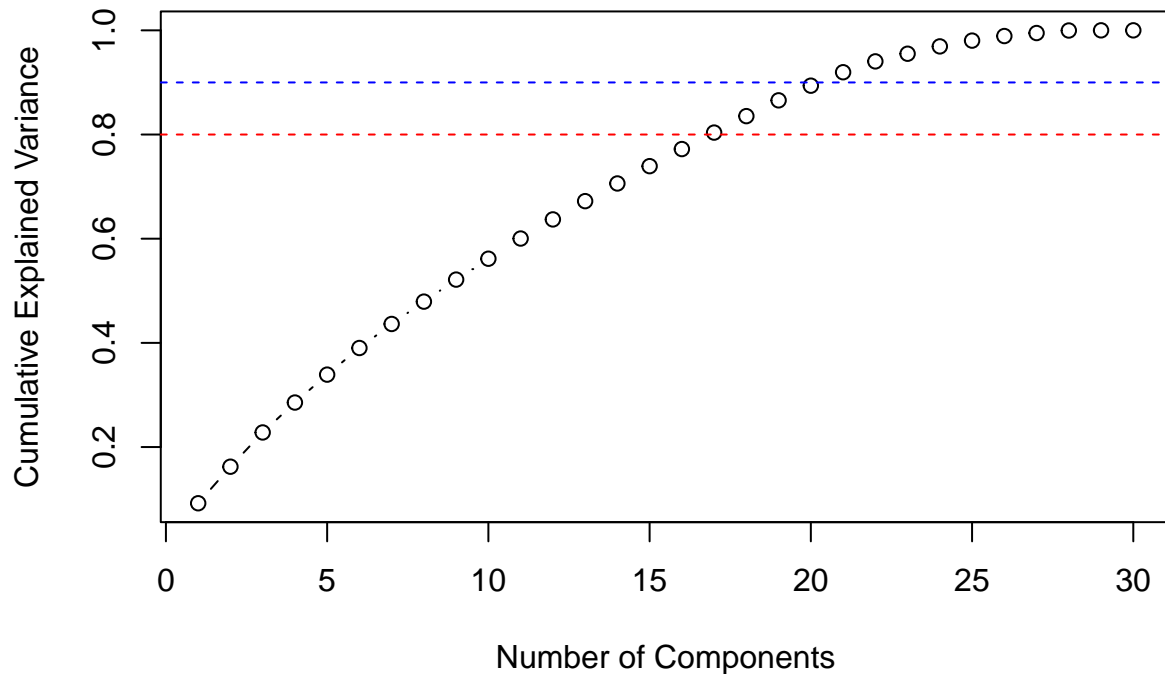
```
# Calculate the proportion of variance explained by each component
explained_variance <- combined_pca_scaled$sdev^2 / sum(combined_pca_scaled$sdev^2)

# Calculate the cumulative explained variance
cumulative_explained_variance <- cumsum(explained_variance)

# Plot the cumulative explained variance
plot(cumulative_explained_variance, type = "b", xlab = "Number of Components", ylab = "Cumulative Explained Variance",
     main = "Cumulative Explained Variance by Principal Components")

# Add a horizontal line for 80% explained variance
abline(h = 0.80, col = "red", lty = 2)
abline(h = 0.90, col = "blue", lty = 2)
```

Cumulative Explained Variance by Principal Components



```
# Determine how many components explain at least 80% variance
components_80 <- which(cumulative_explained_variance >= 0.80)[1]
components_90 <- which(cumulative_explained_variance >= 0.90)[1]

print(paste("Number of components to retain for 80% variance:", components_80))
```

```
## [1] "Number of components to retain for 80% variance: 17"
```

```
print(paste("Number of components to retain for 90% variance:", components_90))
```

```
## [1] "Number of components to retain for 90% variance: 21"
```

```
# Convert categorical variables to dummy variables and remove rows containing "Missing"
combined_data <- merged_data %>%
  mutate(group = if_else(lost == 1, "Lost", "Followed")) %>%
  select(all_of(categorical_vars), group) %>%
  filter(!if_any(all_of(categorical_vars), ~ . == "Missing")) %>%
  mutate(across(all_of(categorical_vars), as.factor))

# Apply model.matrix to convert the categorical variables into dummy variables
combined_data_clean <- model.matrix(~ . - 1, data = combined_data) %>%
  as.data.frame()

# Remove duplicate rows before running t-SNE
combined_data_clean <- combined_data_clean %>%
  distinct()
```

```

# Extract the group information for later plotting
group_labels <- combined_data$group[1:nrow(combined_data_clean)] # Ensure it matches the reduced data

# Perform t-SNE on the dummy variables, setting a perplexity value (typically between 5 and 50)
set.seed(42) # Set seed for reproducibility
tsne_results <- Rtsne(as.matrix(combined_data_clean), dims = 2, perplexity = 10, verbose = TRUE, max_it=

## Performing PCA
## Read the 912 x 31 data matrix successfully!
## OpenMP is working. 1 threads.
## Using no_dims = 2, perplexity = 10.000000, and theta = 0.500000
## Computing input similarities...
## Building tree...
## Done in 0.04 seconds (sparsity = 0.042960)!
## Learning embedding...
## Iteration 50: error is 82.378375 (50 iterations in 0.05 seconds)
## Iteration 100: error is 82.378373 (50 iterations in 0.06 seconds)
## Iteration 150: error is 82.378331 (50 iterations in 0.05 seconds)
## Iteration 200: error is 82.377128 (50 iterations in 0.05 seconds)
## Iteration 250: error is 82.344514 (50 iterations in 0.05 seconds)
## Iteration 300: error is 2.132151 (50 iterations in 0.05 seconds)
## Iteration 350: error is 1.838930 (50 iterations in 0.04 seconds)
## Iteration 400: error is 1.736508 (50 iterations in 0.04 seconds)
## Iteration 450: error is 1.690701 (50 iterations in 0.04 seconds)
## Iteration 500: error is 1.662501 (50 iterations in 0.04 seconds)
## Iteration 550: error is 1.642442 (50 iterations in 0.04 seconds)
## Iteration 600: error is 1.628258 (50 iterations in 0.04 seconds)
## Iteration 650: error is 1.620069 (50 iterations in 0.04 seconds)
## Iteration 700: error is 1.612360 (50 iterations in 0.04 seconds)
## Iteration 750: error is 1.606821 (50 iterations in 0.04 seconds)
## Iteration 800: error is 1.601778 (50 iterations in 0.04 seconds)
## Iteration 850: error is 1.597690 (50 iterations in 0.04 seconds)
## Iteration 900: error is 1.594818 (50 iterations in 0.04 seconds)
## Iteration 950: error is 1.591143 (50 iterations in 0.04 seconds)
## Iteration 1000: error is 1.589428 (50 iterations in 0.04 seconds)
## Fitting performed in 0.87 seconds.

# Convert t-SNE results into a data frame for plotting
tsne_df <- as.data.frame(tsne_results$Y)
colnames(tsne_df) <- c("Dim1", "Dim2")
tsne_df$group <- group_labels

# Plot the t-SNE results using ggplot2
ggplot(tsne_df, aes(x = Dim1, y = Dim2, color = group)) +
  geom_point() +
  labs(title = "t-SNE: Lost vs Followed Groups", x = "t-SNE Dimension 1", y = "t-SNE Dimension 2") +
  theme_minimal()

```

t-SNE: Lost vs Followed Groups

