Week12 IP

Brendah

2022-03-19

1. INTRODUCTION

1.1 Defining the Question

To identify which factors determining whether a user clicks on an ad or not.

1.2 Setting the Metric for Success

The project will be considered a success when I am able to identify what makes a user more likely to click on an ad.

1.3 Outlining the Context

A Kenyan entrepreneur has created an online cryptography course and would want to advertise it on her blog. She currently targets audiences originating from various countries. In the past, she ran ads to advertise a related course on the same blog and collected data in the process. She would now like to employ your services as a Data Science Consultant to help her identify which individuals are most likely to click on her ads.

1.4 Drafting the Experimental Design

1. Define the question, the metric for success, the context, experimental design taken and the appropriateness of the available data to answer the given question.
2. Load the dataset and previewing it.
3. Check for missing and duplicated values and deal with them where necessary.
4. Check for outliers and other anomalies and deal with them where necessary.
5. Perform univariate and bivariate analysis.
6. Conclude .

1.5 Determining the Appropriateness of the Data

2. Data Preparation and Cleaning

```
#data<- advertising
#head(data)
data <- read.csv('http://bit.ly/IPAdvertisingData')
head(data)
```

```
##   Daily.Time.Spent.on.Site Age Area.Income Daily.Internet.Usage
## 1                    68.95  35    61833.90               256.09
## 2                    80.23  31    68441.85               193.77
## 3                    69.47  26    59785.94               236.50
## 4                    74.15  29    54806.18               245.89
## 5                    68.37  35    73889.99               225.58
## 6                    59.99  23    59761.56               226.74
##                          Ad.Topic.Line           City Male    Country
## 1    Cloned 5thgeneration orchestration    Wrightburgh    0    Tunisia
## 2    Monitored national standardization      West Jodi    1      Nauru
## 3      Organic bottom-line service-desk       Davidton    0 San Marino
## 4 Triple-buffered reciprocal time-frame West Terrifurt    1      Italy
## 5         Robust logistical utilization   South Manuel    0    Iceland
## 6       Sharable client-driven software      Jamieberg    1     Norway
##             Timestamp Clicked.on.Ad
## 1 2016-03-27 00:53:11             0
## 2 2016-04-04 01:39:02             0
## 3 2016-03-13 20:35:42             0
## 4 2016-01-10 02:31:19             0
## 5 2016-06-03 03:36:18             0
## 6 2016-05-19 14:30:17             0
```

```
#to check the number of rows and columns in the dataset
dim(data)
```

```
## [1] 1000   10
```

We can see that there are 1000 rows and 10 columns

```
#to show the structure of the data set specifically the data types of the columns
str(data)
```

```
## 'data.frame':    1000 obs. of  10 variables:
##  $ Daily.Time.Spent.on.Site: num  69 80.2 69.5 74.2 68.4 ...
##  $ Age                     : int  35 31 26 29 35 23 33 48 30 20 ...
##  $ Area.Income             : num  61834 68442 59786 54806 73890 ...
##  $ Daily.Internet.Usage    : num  256 194 236 246 226 ...
##  $ Ad.Topic.Line           : chr  "Cloned 5thgeneration orchestration" "Monitored national standardi
##  $ City                    : chr  "Wrightburgh" "West Jodi" "Davidton" "West Terrifurt" ...
##  $ Male                    : int  0 1 0 1 0 1 0 1 1 1 ...
##  $ Country                 : chr  "Tunisia" "Nauru" "San Marino" "Italy" ...
##  $ Timestamp               : chr  "2016-03-27 00:53:11" "2016-04-04 01:39:02" "2016-03-13 20:35:42"
##  $ Clicked.on.Ad           : int  0 0 0 0 0 0 0 1 0 0 ...
```

The dataset contains 3 num, 3 int and 4 chr variable datatypes

I will change the column names and then change the "Male" and "Clicked on Ad" columns to be categorical variables (Factors) instead of numerical variables . The modification will be to make the dataset easier to work with

```
# get column names
colnames(data)
```

```
##  [1] "Daily.Time.Spent.on.Site" "Age"
##  [3] "Area.Income"              "Daily.Internet.Usage"
##  [5] "Ad.Topic.Line"            "City"
##  [7] "Male"                     "Country"
##  [9] "Timestamp"                "Clicked.on.Ad"
```

```
# rename them
names(data)[names(data) == "Daily.Time.Spent.on.Site"] <- "daily_time_spent"
names(data)[names(data) == "Age"] <- "age"
names(data)[names(data) == "Area.Income"] <- "area_income"
names(data)[names(data) == "Daily.Internet.Usage"] <- "daily_internet_usage"
names(data)[names(data) == "Ad.Topic.Line"] <- "ad_topic_line"
names(data)[names(data) == "City"] <- "city"
names(data)[names(data) == "Male"] <- "male"
names(data)[names(data) == "Country"] <- "country"
names(data)[names(data) == "Timestamp"] <- "timestamp"
names(data)[names(data) == "Clicked.on.Ad"] <- "clicked_on_ad"
#to confirm they've been changed
colnames(data)
```

```
##  [1] "daily_time_spent"     "age"                  "area_income"
##  [4] "daily_internet_usage" "ad_topic_line"        "city"
##  [7] "male"                 "country"              "timestamp"
## [10] "clicked_on_ad"
```

```
# changing the data types of the "male" and "clicked_on_ad" columns from integer to categorical
data$male <- as.factor(data$male)
data$clicked_on_ad<-as.factor(data$clicked_on_ad)
head(data)
```

```
##   daily_time_spent age area_income daily_internet_usage
## 1            68.95  35    61833.90               256.09
## 2            80.23  31    68441.85               193.77
## 3            69.47  26    59785.94               236.50
## 4            74.15  29    54806.18               245.89
## 5            68.37  35    73889.99               225.58
## 6            59.99  23    59761.56               226.74
##                          ad_topic_line           city male    country
## 1    Cloned 5thgeneration orchestration    Wrightburgh    0    Tunisia
## 2    Monitored national standardization      West Jodi    1      Nauru
## 3      Organic bottom-line service-desk       Davidton    0 San Marino
## 4 Triple-buffered reciprocal time-frame West Terrifurt    1      Italy
## 5         Robust logistical utilization   South Manuel    0    Iceland
## 6       Sharable client-driven software      Jamieberg    1     Norway
##             timestamp clicked_on_ad
## 1 2016-03-27 00:53:11             0
## 2 2016-04-04 01:39:02             0
## 3 2016-03-13 20:35:42             0
## 4 2016-01-10 02:31:19             0
## 5 2016-06-03 03:36:18             0
## 6 2016-05-19 14:30:17             0
```

```
str(data)
```

```
## 'data.frame':    1000 obs. of  10 variables:
##  $ daily_time_spent    : num  69 80.2 69.5 74.2 68.4 ...
##  $ age                 : int  35 31 26 29 35 23 33 48 30 20 ...
##  $ area_income         : num  61834 68442 59786 54806 73890 ...
##  $ daily_internet_usage: num  256 194 236 246 226 ...
##  $ ad_topic_line       : chr  "Cloned 5thgeneration orchestration" "Monitored national standardizati
##  $ city                : chr  "Wrightburgh" "West Jodi" "Davidton" "West Terrifurt" ...
##  $ male                : Factor w/ 2 levels "0","1": 1 2 1 2 1 2 1 2 2 2 ...
##  $ country             : chr  "Tunisia" "Nauru" "San Marino" "Italy" ...
##  $ timestamp           : chr  "2016-03-27 00:53:11" "2016-04-04 01:39:02" "2016-03-13 20:35:42" "201
##  $ clicked_on_ad       : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 2 1 1 ...
```

We can now see that the data types of the columns 'male' and 'clicked_on_ad' have changed from int to Factor(categorical)

```
# checking for duplicates
anyDuplicated(data)
```

```
## [1] 0
```

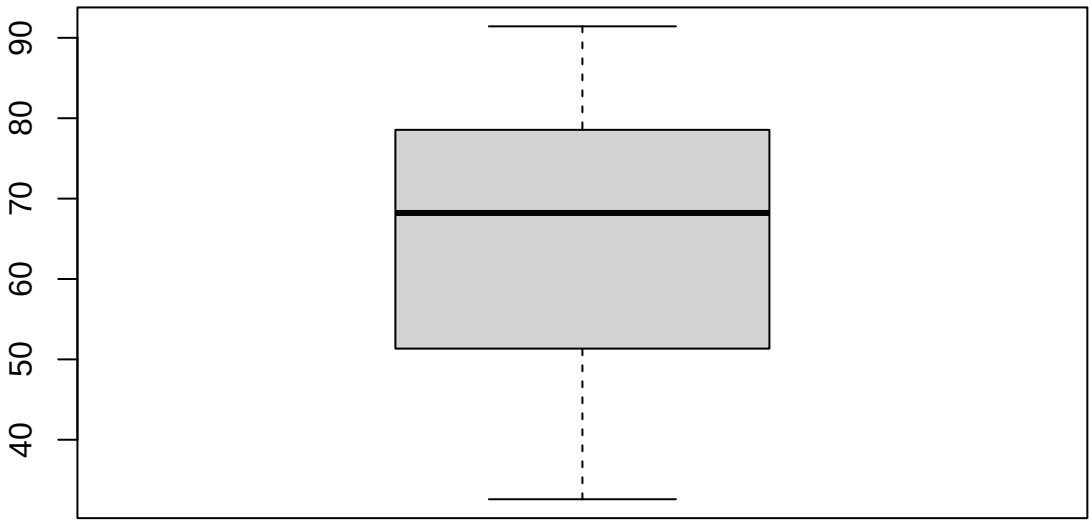
There are no duplicates

```
# looking for missing values
colSums(is.na(data))
```

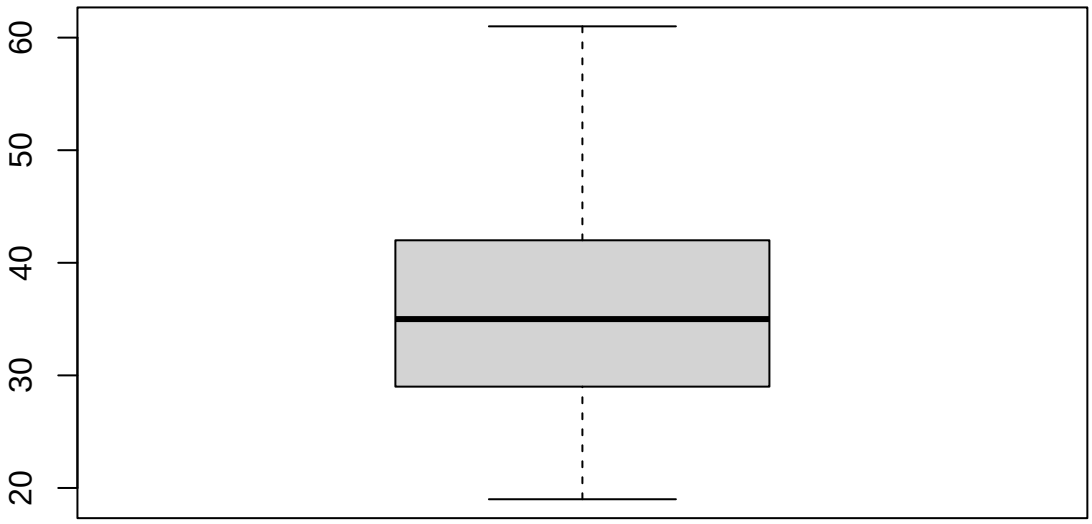
```
##     daily_time_spent                  age          area_income
##                    0                    0                    0
## daily_internet_usage        ad_topic_line                 city
##                    0                    0                    0
##                 male              country            timestamp
##                    0                    0                    0
##        clicked_on_ad
##                    0
```

There are no missing values in each column

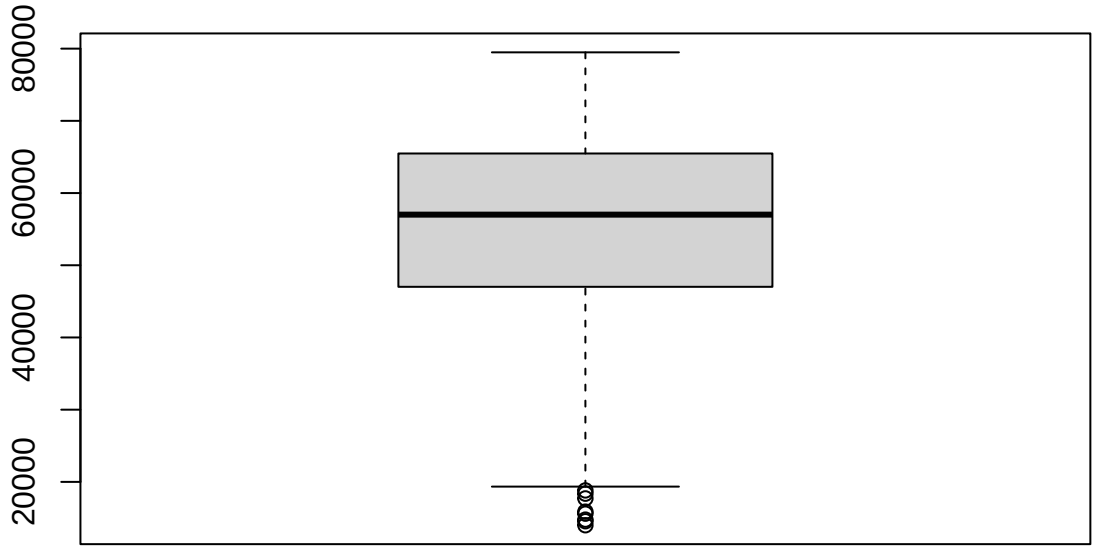
```
# Using boxplot to check for outliers of numerical variables
boxplot(data$daily_time_spent)
```



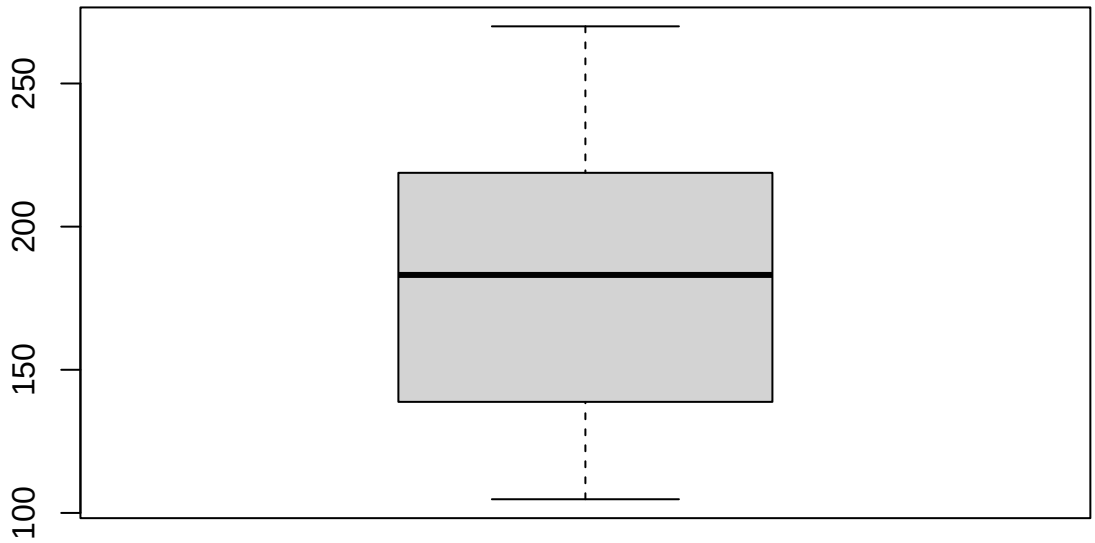

```
boxplot(data$age)
```




```
boxplot(data$area_income)
```




```
boxplot(data$daily_internet_usage)
```




```
#check for anomalies
unique_male<-unique(data$male)
unique_male
```

```
## [1] 0 1
## Levels: 0 1
```

3. Exploratory Data Analysis

3.1 Univariate Analysis

```
#summary of all columns
summary(data)
```

```
##  daily_time_spent      age         area_income    daily_internet_usage
##  Min.   :32.60    Min.   :19.00   Min.   :13996   Min.   :104.8
##  1st Qu.:51.36    1st Qu.:29.00   1st Qu.:47032   1st Qu.:138.8
##  Median :68.22    Median :35.00   Median :57012   Median :183.1
##  Mean   :65.00    Mean   :36.01   Mean   :55000   Mean   :180.0
##  3rd Qu.:78.55    3rd Qu.:42.00   3rd Qu.:65471   3rd Qu.:218.8
##  Max.   :91.43    Max.   :61.00   Max.   :79485   Max.   :270.0
##  ad_topic_line          city           male      country
##  Length:1000        Length:1000        0:519   Length:1000
```

```
##  Class :character   Class :character   1:481   Class :character
##  Mode  :character   Mode  :character           Mode  :character
##
##
##
##   timestamp         clicked_on_ad
##  Length:1000        0:500
##  Class :character   1:500
##  Mode  :character
##
##
##
```

```
# getting the minimum, maximum, mean,median and quartiles
summary(data$daily_time_spent)
```

3.1.1 Daily Time Spent

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   32.60   51.36   68.22   65.00   78.55   91.43
```

```
# create function to calculate mode since R doesn't have an in-built function to do that
getmode <- function(v) {
   uniqv <- unique(v)
   uniqv[which.max(tabulate(match(v, uniqv)))]
}
# now calling the mode function on our column
getmode(data$daily_time_spent)
```

```
## [1] 62.26
```

```
# find variance
var(data$daily_time_spent)
```

```
## [1] 251.3371
```

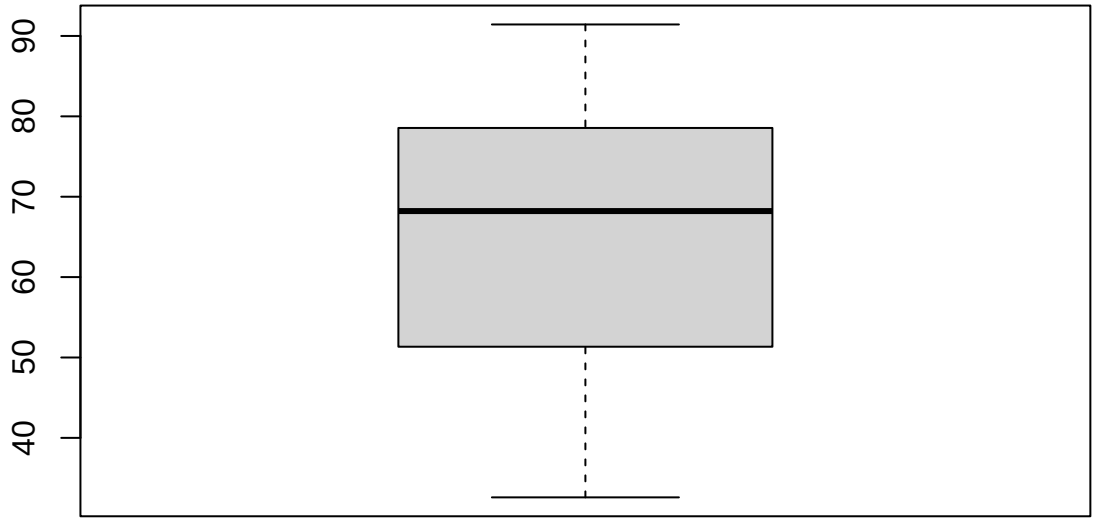
```
# find standard deviation
sd(data$daily_time_spent)
```

```
## [1] 15.85361
```

```
# get interquantile range
quantile(data$daily_time_spent, 0.75) - quantile(data$daily_time_spent, 0.25)
```

```
##     75%
## 27.1875
```

```
# graph boxplot
boxplot(data$daily_time_spent)
```



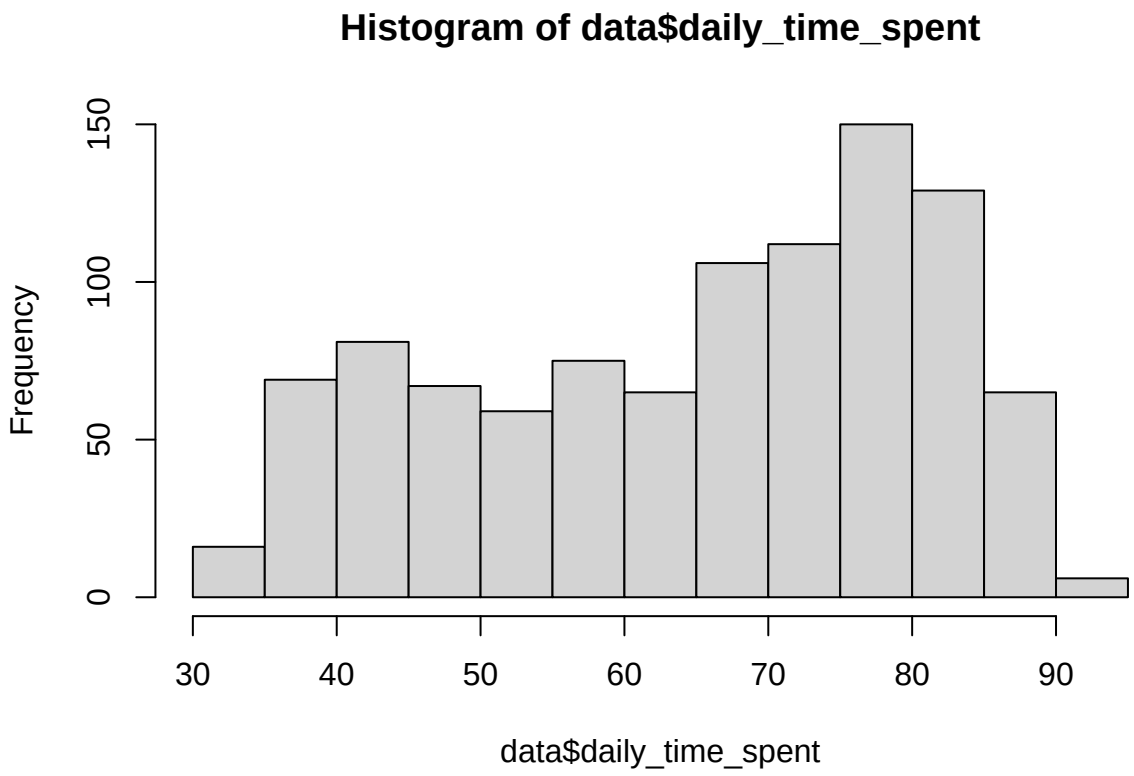
This variable does not have any outliers.

```
# find the kurtosis of this variable

library(moments)
kurtosis(data$daily_time_spent)
```

```
## [1] 1.903942
```

This kurtosis value is less than 3 implying that the distribution of this variable is platykurtic which means that there are few to no outliers.

```
# check distribution
hist(data$daily_time_spent)
```




```
skewness(data$daily_time_spent)
```

```
## [1] -0.3712026
```

This variable is slightly negatively skewed.

```
# getting the minimum, maximum, mean,median and quartiles
summary(data$age)
```

3.1.2 Age

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   19.00   29.00   35.00   36.01   42.00   61.00
```

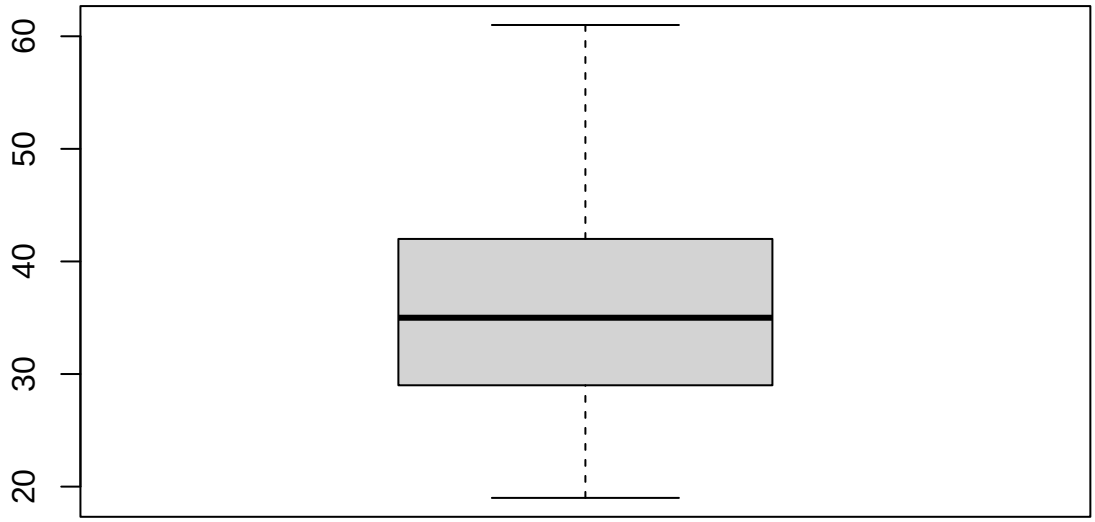
```
# getting mode
getmode(data$age)
```

```
## [1] 31
```

```
# standard deviation
sd(data$age)
```

```
## [1] 8.785562
```

```
# check for outliers
boxplot(data$age)
```



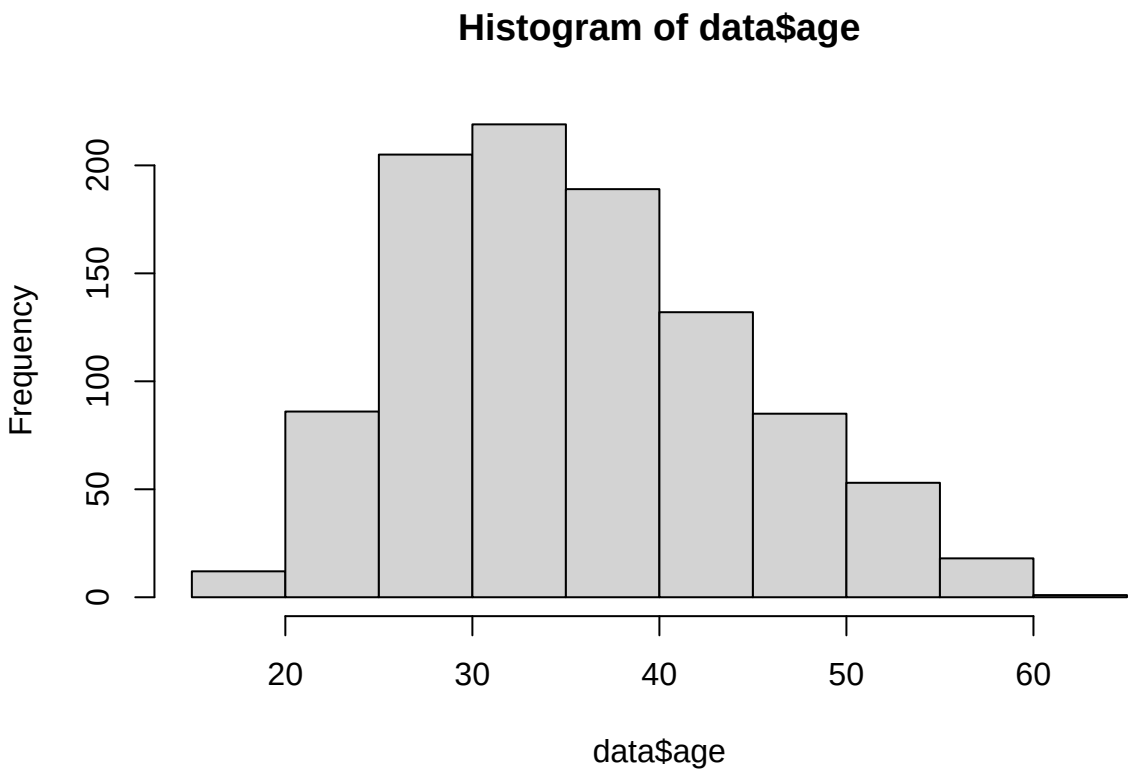
No outliers.

```
# check kurtosis
kurtosis(data$age)
```

```
## [1] 2.595482
```

The distribution is platykurtic implying the existence of few to no outliers.

```
# check distribution
hist(data$age)
```



The distribution looks almost normal

```
skewness(data$age)
```

```
## [1] 0.4784227
```

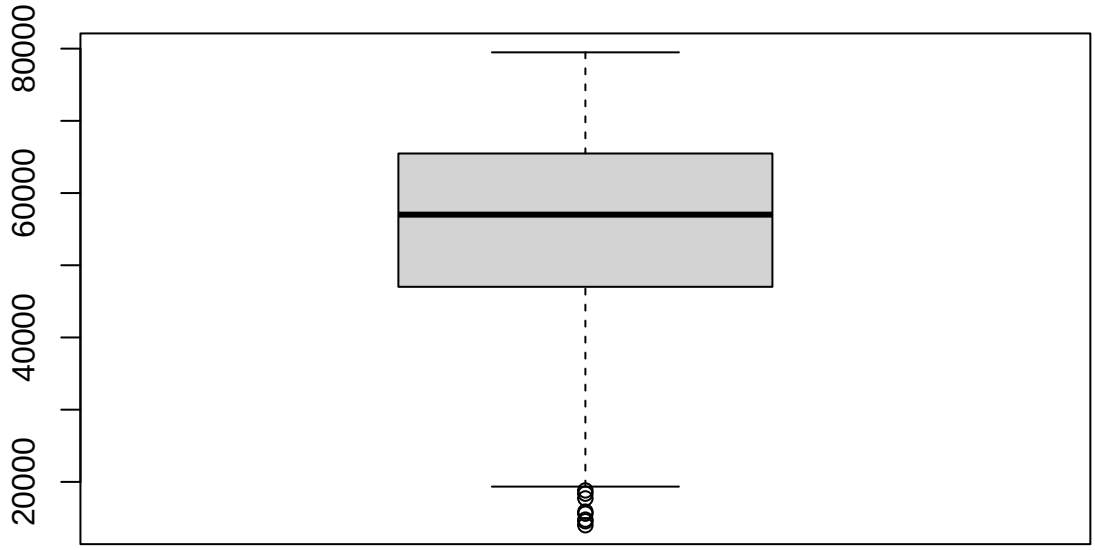
This skewness value implies that the distribution is almost fairly symmetrical unlike our observation from the histogram distribution where it looks almost normal

```
# getting the minimum, maximum, mean,median and quartiles
summary(data$area_income)
```

3.1.3 Area Income

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   13996   47032   57012   55000   65471   79485
```

```
# check for outliers
boxplot(data$area_income)
```



There are outliers below the 20,000 mark.

```
# getting mode
getmode(data$area_income)
```

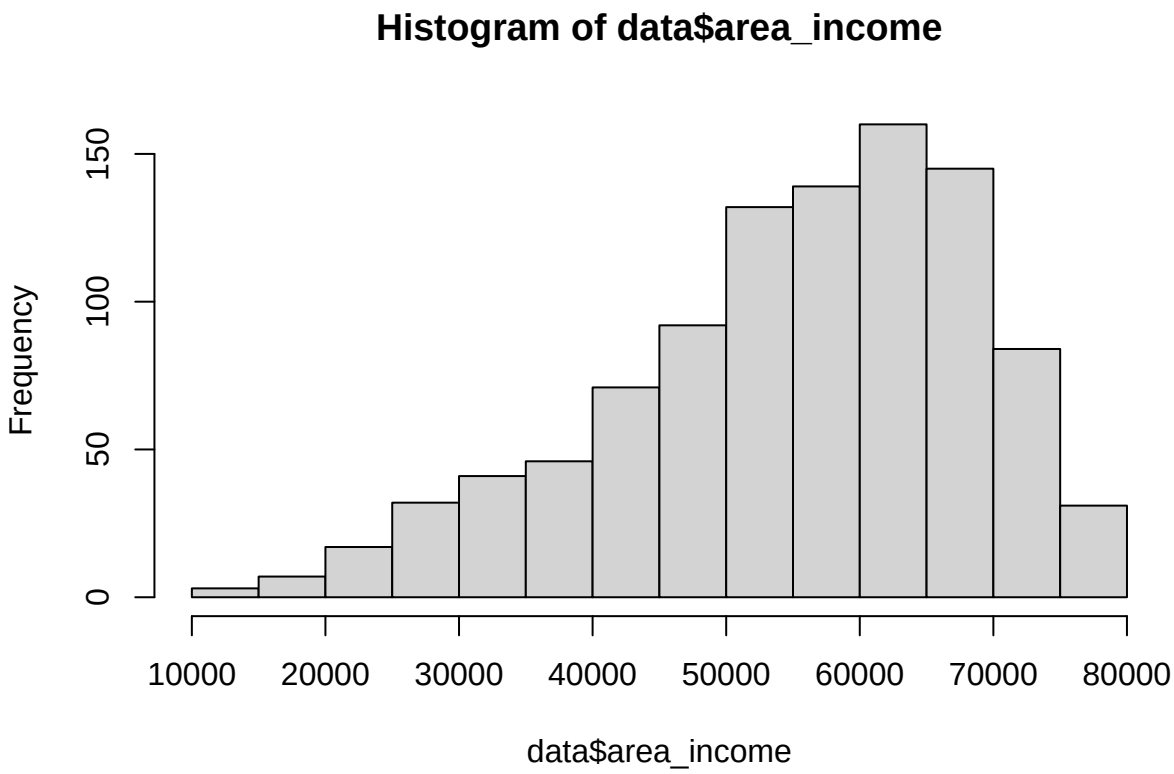
```
## [1] 61833.9
```

```
# check kurtosis
kurtosis(data$area_income)
```

```
## [1] 2.894694
```

A kurtosis value of 2.89 indicates that the distribution is platykurtic although it is getting very close to being mesokurtic.

```
# check distribution
hist(data$area_income)
```



The distribution is negatively skewed.

```
# check skewness
skewness(data$area_income)
```

```
## [1] -0.6493967
```

it's indeed negatively skewed

```
# getting the minimum, maximum, mean,median and quartiles
summary(data$daily_internet_usage)
```

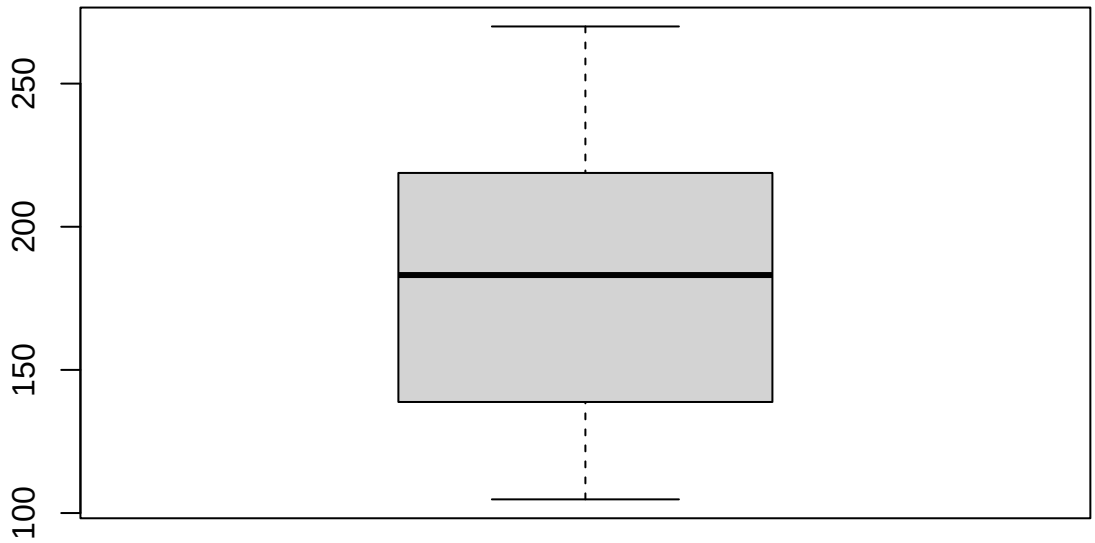
3.1.4 Daily Internet Usage

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   104.8   138.8   183.1   180.0   218.8   270.0
```

```
# getting mode
getmode(data$daily_internet_usage)
```

```
## [1] 167.22
```

```
# check for outliers
boxplot(data$daily_internet_usage)
```



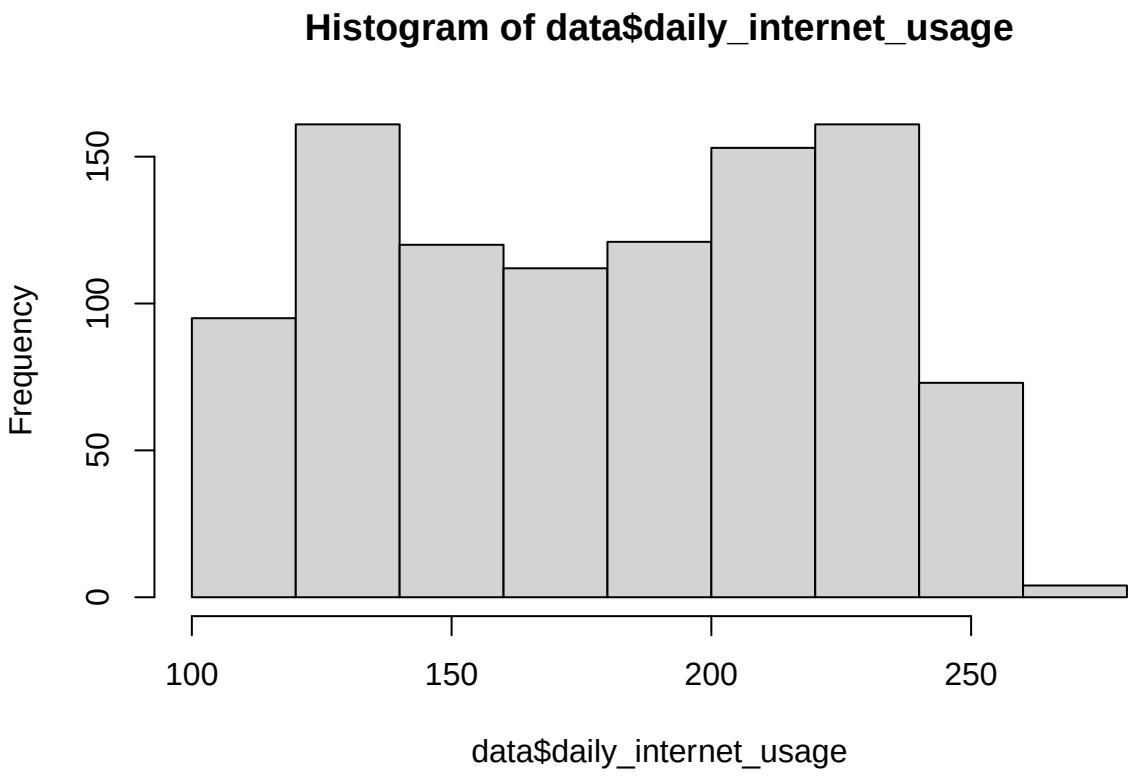
There are no outliers in this column.

```
# check kurtosis
kurtosis(data$daily_internet_usage)
```

```
## [1] 1.727701
```

The distribution is platykurtic.

```
# check distribution
hist(data$daily_internet_usage)
```



The distribution appears to be relatively uniform and bimodal.

```
# check skewness
skewness(data$daily_internet_usage)
```

```
## [1] -0.03348703
```

```
# displaying the first 6 frequently occurring cities
 library(plyr)
count_city <- count(data$city)
count_city_head <- head(arrange(count_city, desc(freq)))
count_city_head
```

3.1.5 city

```
##                 x freq
## 1       Lisamouth    3
## 2    Williamsport    3
## 3 Benjaminchester    2
## 4       East John    2
## 5    East Timothy    2
## 6        Johnstad    2
```

Lisamouth,Williamsport,Benjaminchester,East John,East Timothy and Johnstad are 6 frequently occurring cities

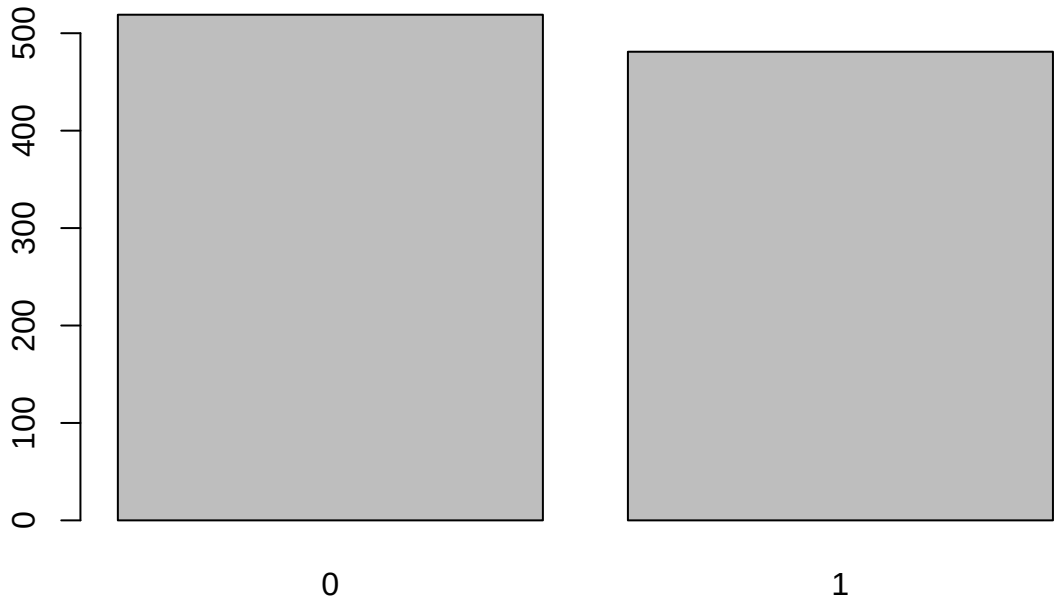
```
male_table <- table(data$male)
male_table
```

3.1.6 male

```
##
##   0   1
## 519 481
```

We see here that 519 are not male while 481 are. To easily visualize this:

```
barplot(male_table)
```




```
# displaying the first 10 frequently occuring countries
count_country <- count(data$country)
count_country_head <- head(arrange(count_country, desc(freq)), 10)
count_country_head
```

3.1.7 country

```
##                 x freq
## 1  Czech Republic    9
## 2          France    9
## 3     Afghanistan    8
## 4       Australia    8
## 5          Cyprus    8
## 6          Greece    8
## 7         Liberia    8
## 8      Micronesia    8
## 9            Peru    8
## 10        Senegal    8
```

The table displays the 10 frequently occuring countries with Czech Republic and France leading

```
ad_table <- table(data$clicked_on_ad)
print(ad_table)
```

3.1.8 clicked on ad

```
##
##   0   1
## 500 500
```

People who both clicked on the ad and didn't click on the ad is the same (500 each).

3.2 Bivariate Analysis

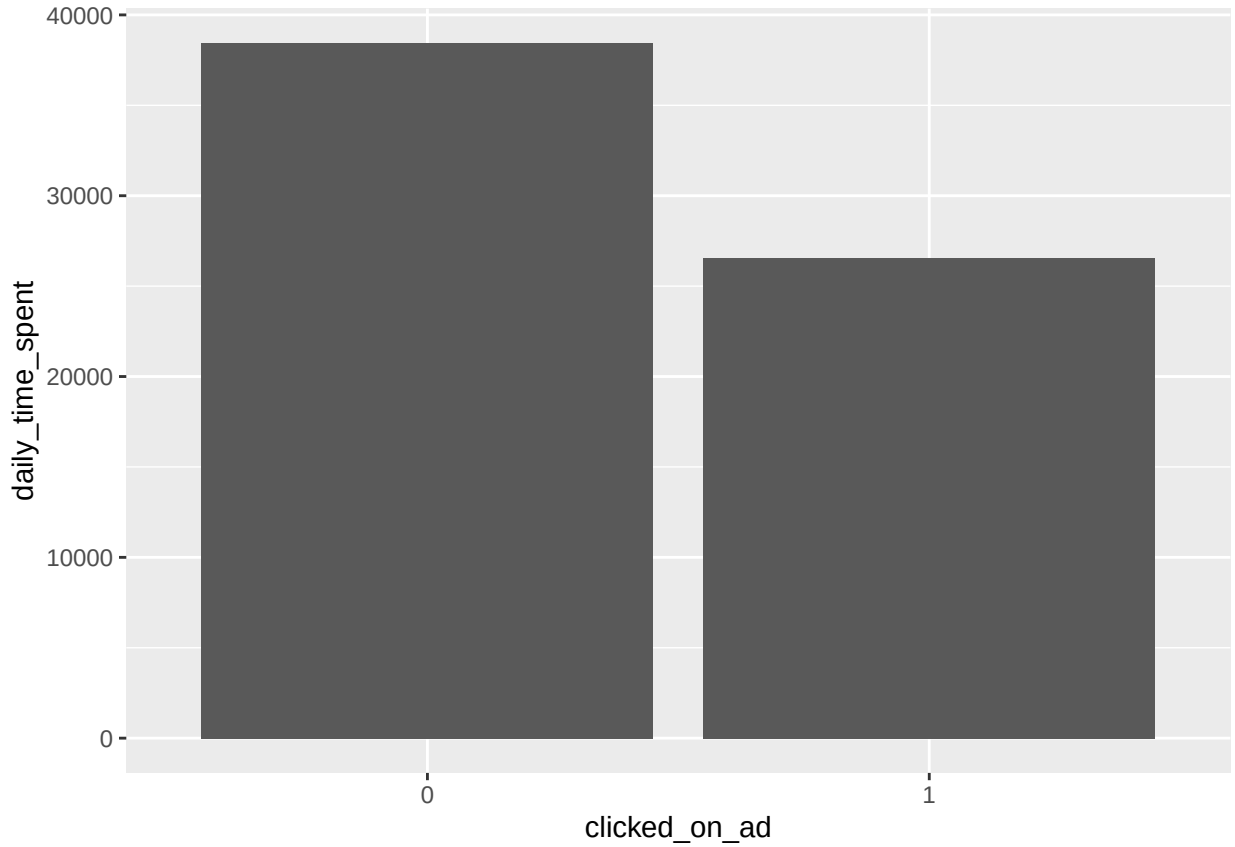
3.2.1 Research-specific Bivariate Analysis relationship between our target variable (clicked_on_ad) and the other variables.

```
# how many males clicked on ads
ad_male.table <- table(data$clicked_on_ad, data$male)
names(dimnames(ad_male.table)) <- c("Clicked on Ad?", "Male?")
ad_male.table
```

```
##               Male?
## Clicked on Ad?   0   1
##              0 250 250
##              1 269 231
```

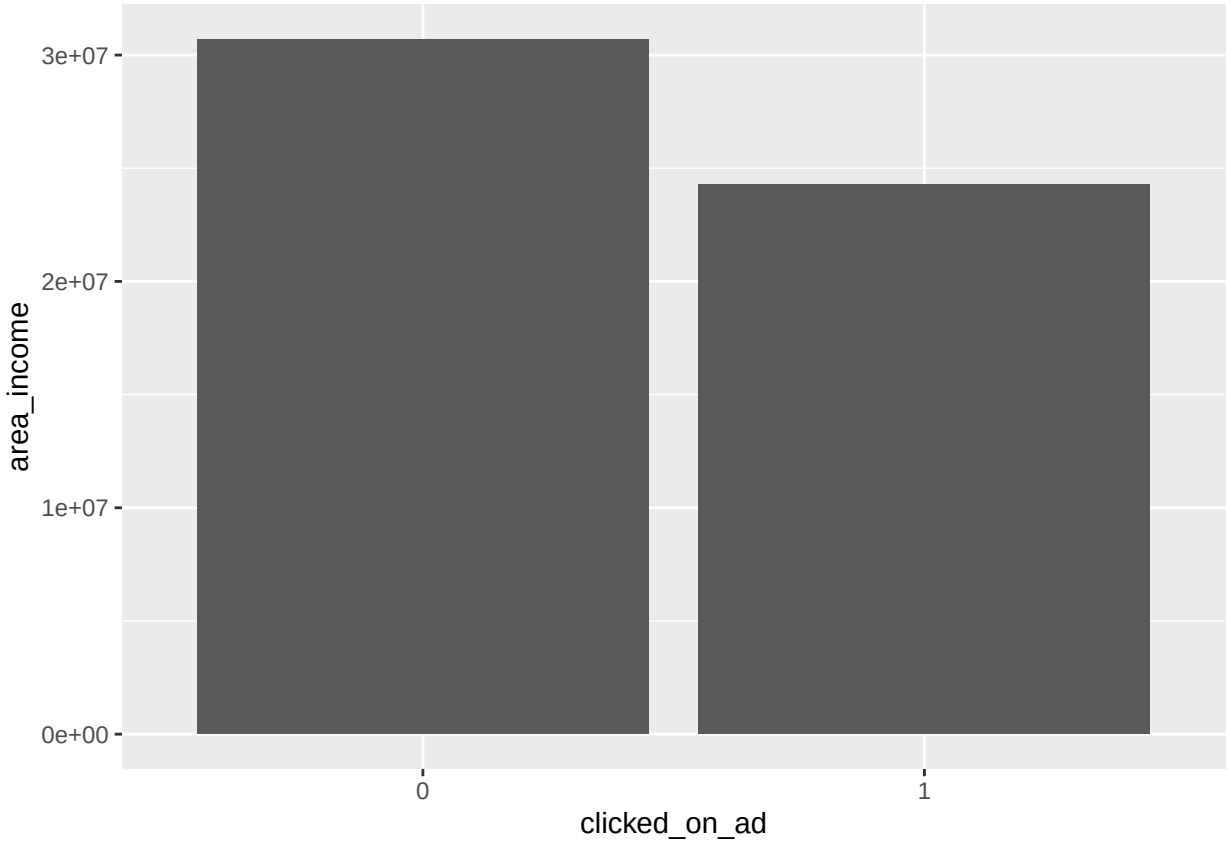
From this we see that of those who clicked on the ad, 269 were female while 231 were male. There was no difference in gender of those who did not click on the ad.

```
library(ggplot2);
ggplot(data, aes(clicked_on_ad,daily_time_spent)) +
    geom_bar(stat ="identity") +
    labs(y ="daily_time_spent",x ="clicked_on_ad")
```



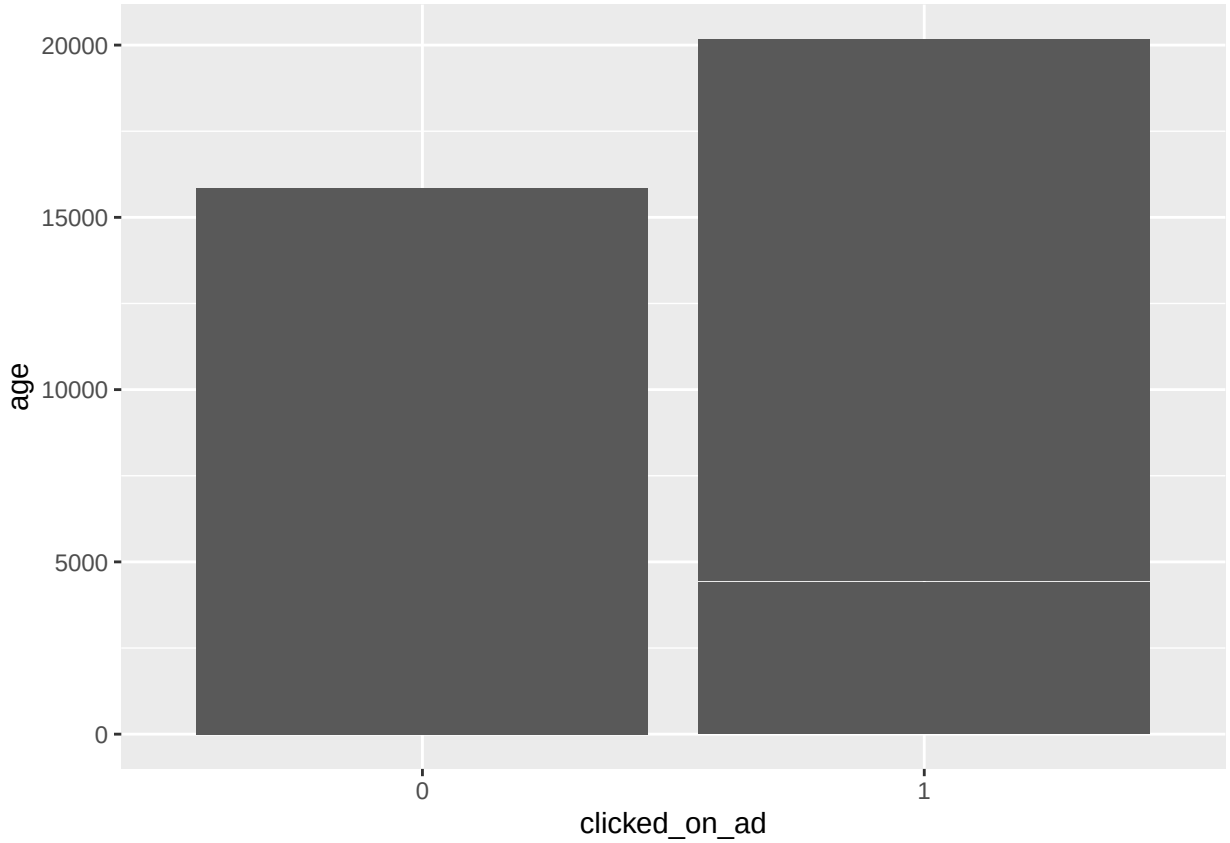
People who spent more time on the site did not click on the ad compared those who did.

```
ggplot(data, aes(clicked_on_ad, area_income)) +
    geom_bar(stat = "identity") +
    labs(y = "area_income", x = "clicked_on_ad")
```



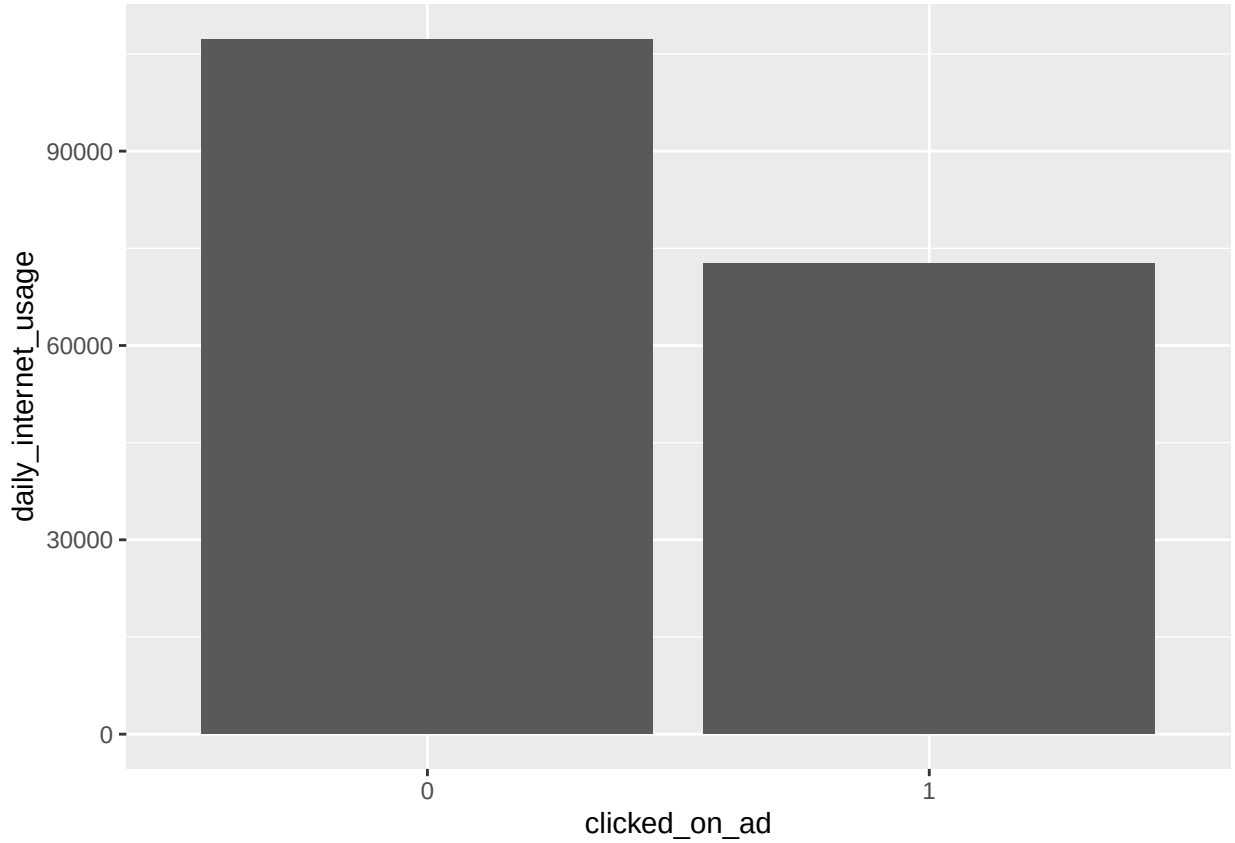
The higher the area income the lower the clicked ads and vice versa.

```
ggplot(data, aes(clicked_on_ad, age)) +
    geom_bar(stat = "identity") +
    labs(y = "age", x = "clicked_on_ad")
```



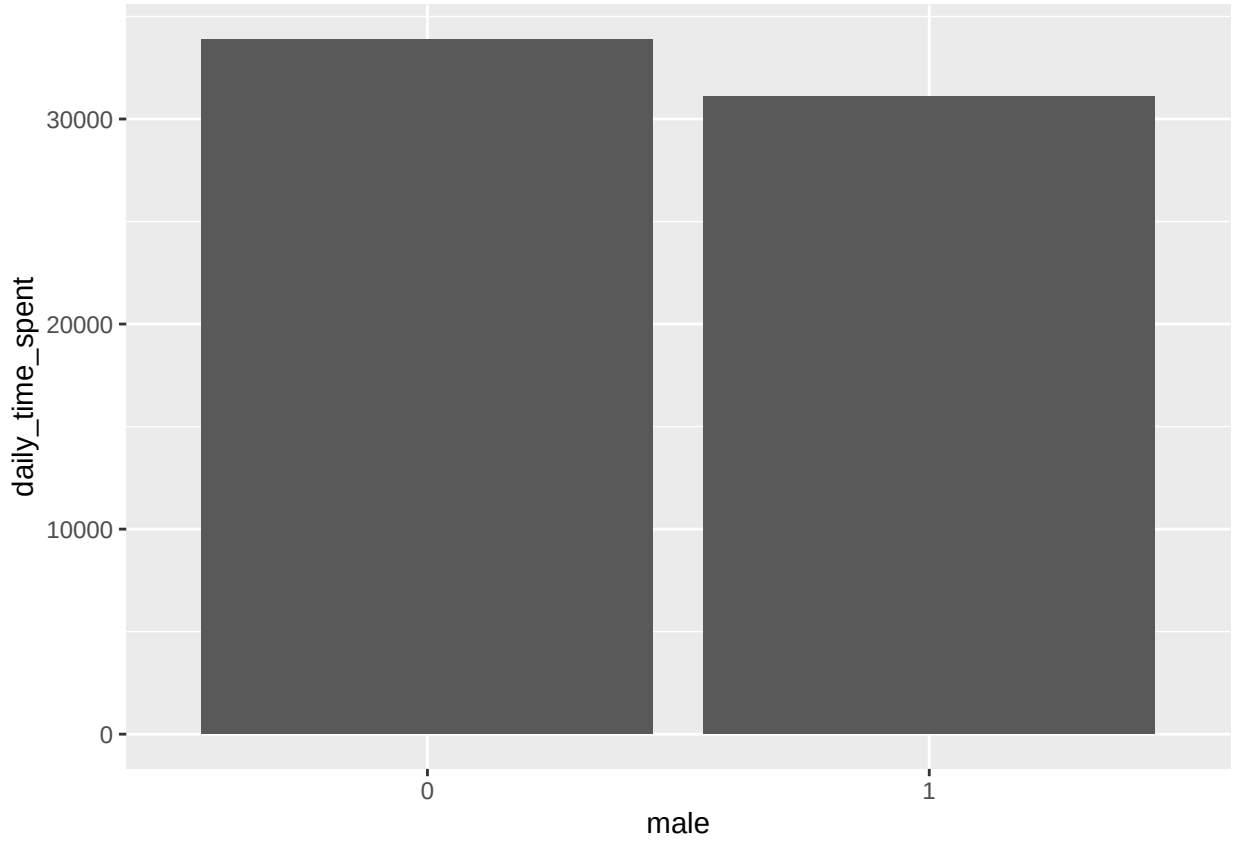
Older people clicked on ads compared to younger people.

```
ggplot(data, aes(clicked_on_ad, daily_internet_usage)) +
    geom_bar(stat = "identity") +
    labs(y = "daily_internet_usage", x = "clicked_on_ad")
```



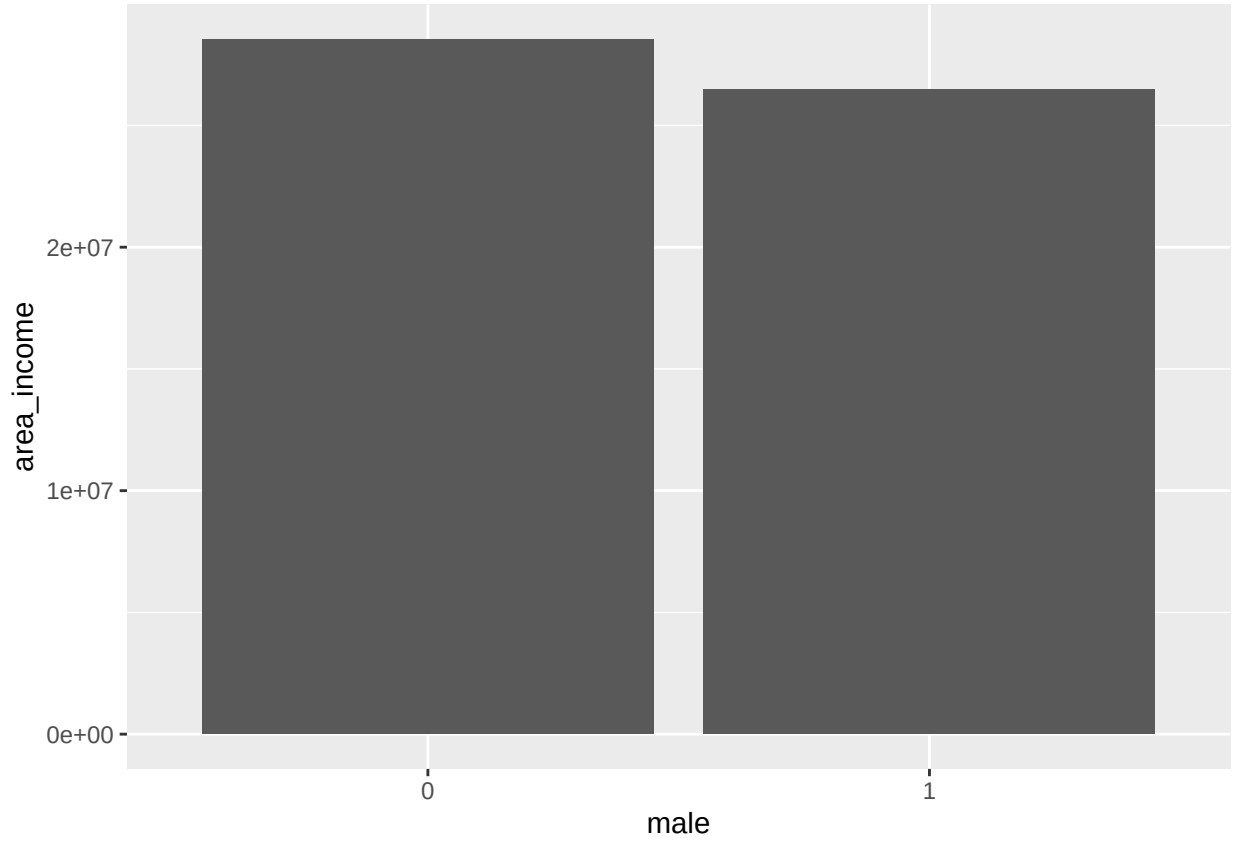
High internet usage did not necessarily mean higher clicks.

```
# a. Using Male Category

# Using bar charts to show the relationship between the Male and other independent variables.

library(ggplot2);
ggplot(data, aes(male,daily_time_spent)) +
    geom_bar(stat = "identity") +
    labs(y ="daily_time_spent",x ="male")
```



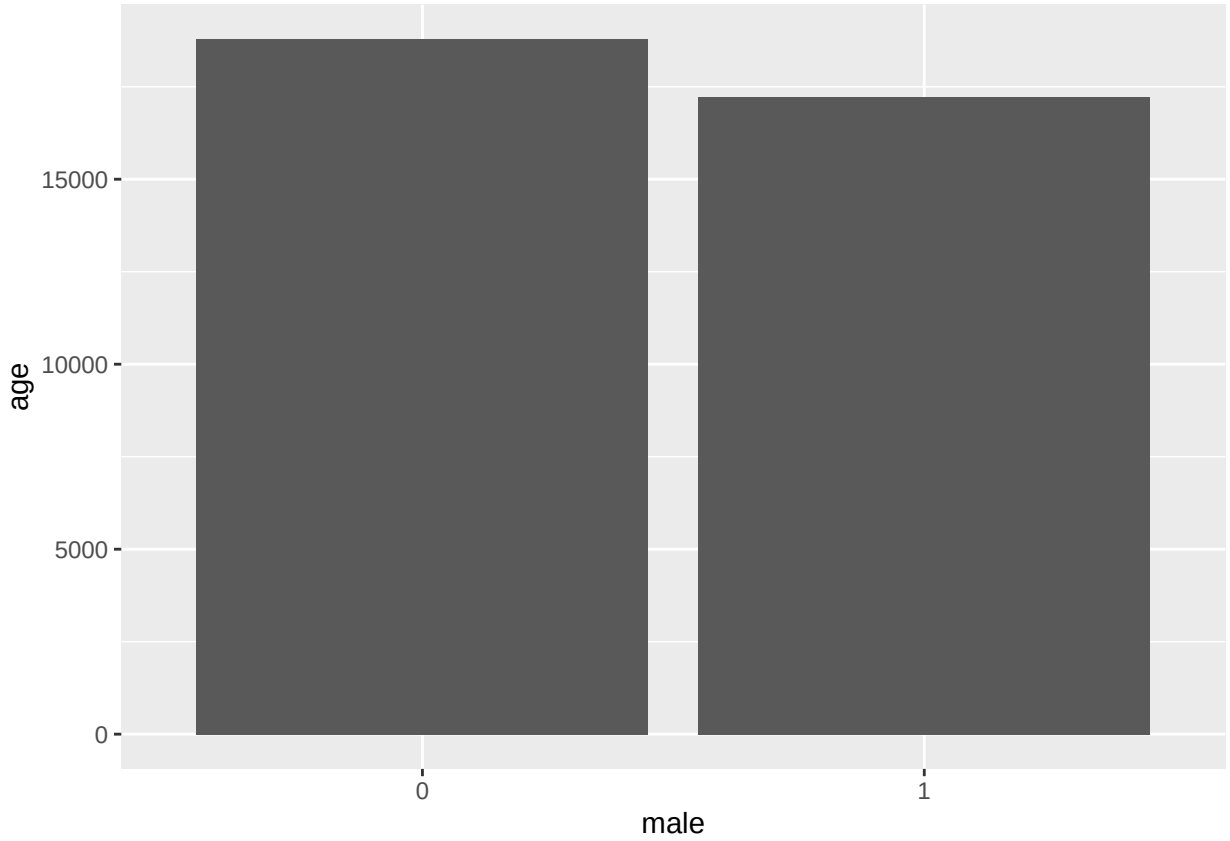
Non-males spend more time on the site compared to the males.

```
ggplot(data, aes(male, area_income)) +
    geom_bar(stat = "identity") +
    labs(y = "area_income", x = "male")
```



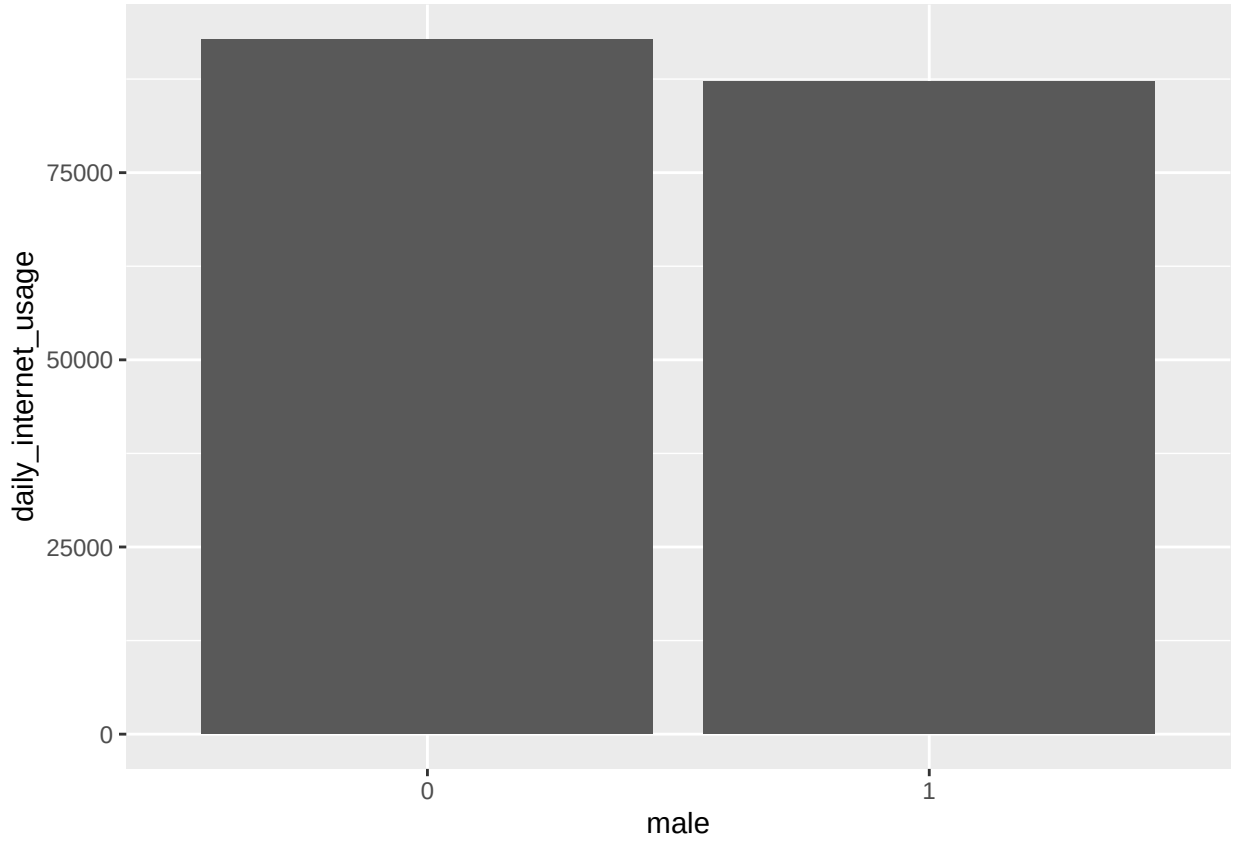
Males have lower area income compared to non-males.

```
ggplot(data, aes(male, age)) +
    geom_bar(stat = "identity") +
    labs(y = "age", x = "male")
```



Older folk are more of non-males than males.

```
ggplot(data, aes(male, daily_internet_usage)) +
    geom_bar(stat = "identity") +
    labs(y = "daily_internet_usage", x = "male")
```



Males use less internet compared to the other gender.

```
colnames(data)
```

```
##  [1] "daily_time_spent"     "age"                  "area_income"
##  [4] "daily_internet_usage" "ad_topic_line"        "city"
##  [7] "male"                 "country"              "timestamp"
## [10] "clicked_on_ad"
```

4. Conclusion

We will use the results we have obtained from our exploratory data analysis to make conclusions.

To begin with, we see that the dataset was already slightly biased by having slightly more females than males. Because of this, more females than males clicked on the ad.

People with lower area incomes clicked more on the ad than people with higher area incomes.

People who spent less time online were more likely to click on the ad than people who spent more time online.