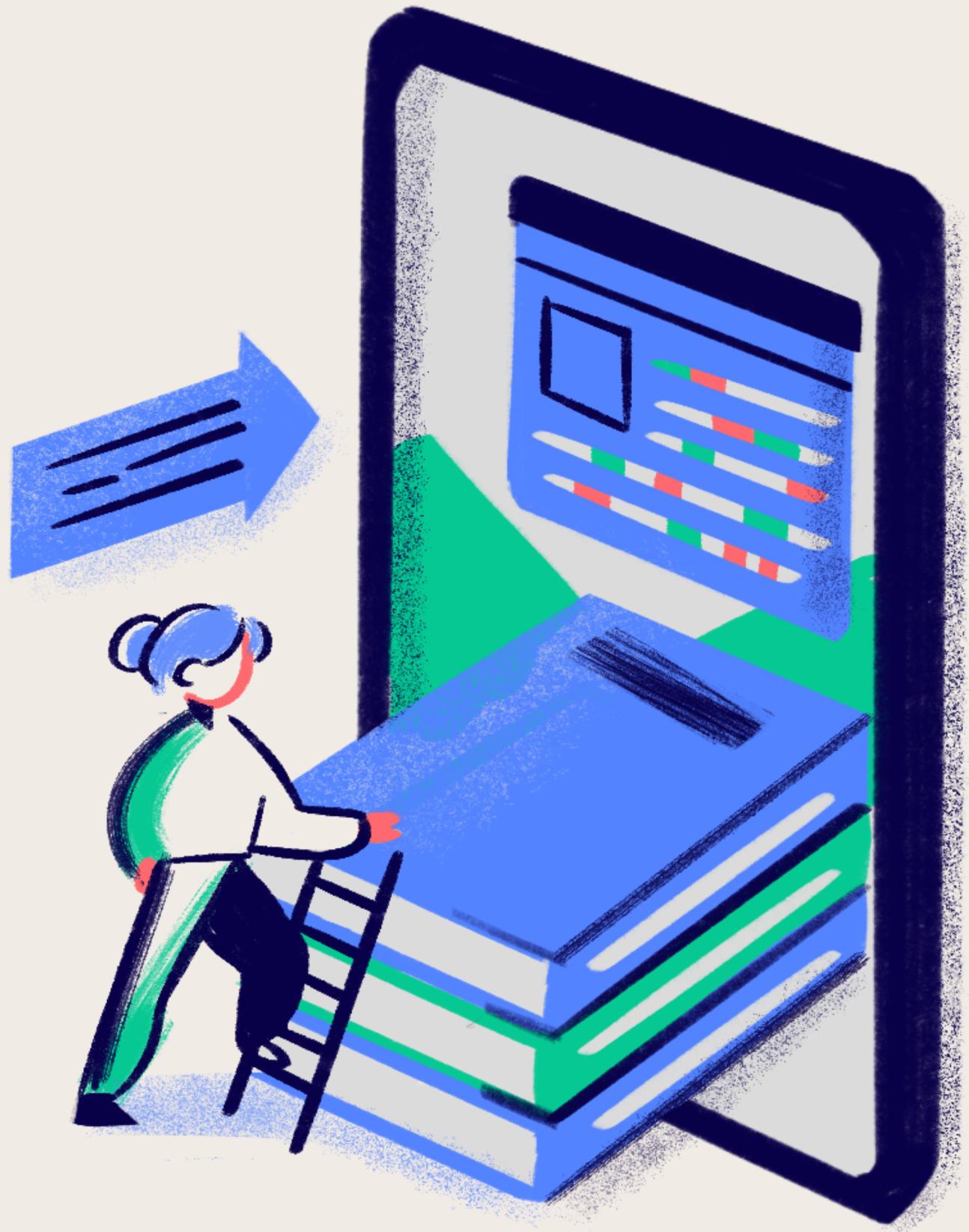


# Business Analytics & Research (using R)



# **PRESENTED BY:**

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# Research Project of BAR with R



# Themes Brainstormed

- Artificial Intelligence
- IOT
- Virtual Reality
- Metaverse
- Neuroscience
- Tech. Adoption
- Consumer Behavior



# Theme Selected

Technology Adoption ✓



## Topics Brainstormed

Natural Language Processing:  
a revolution in computer-human communication

Impact of metaverse on consumer behavior

Autonomous Driving Using common sense reasoning

The future of computer-assisted education

The risks of Digital Voting

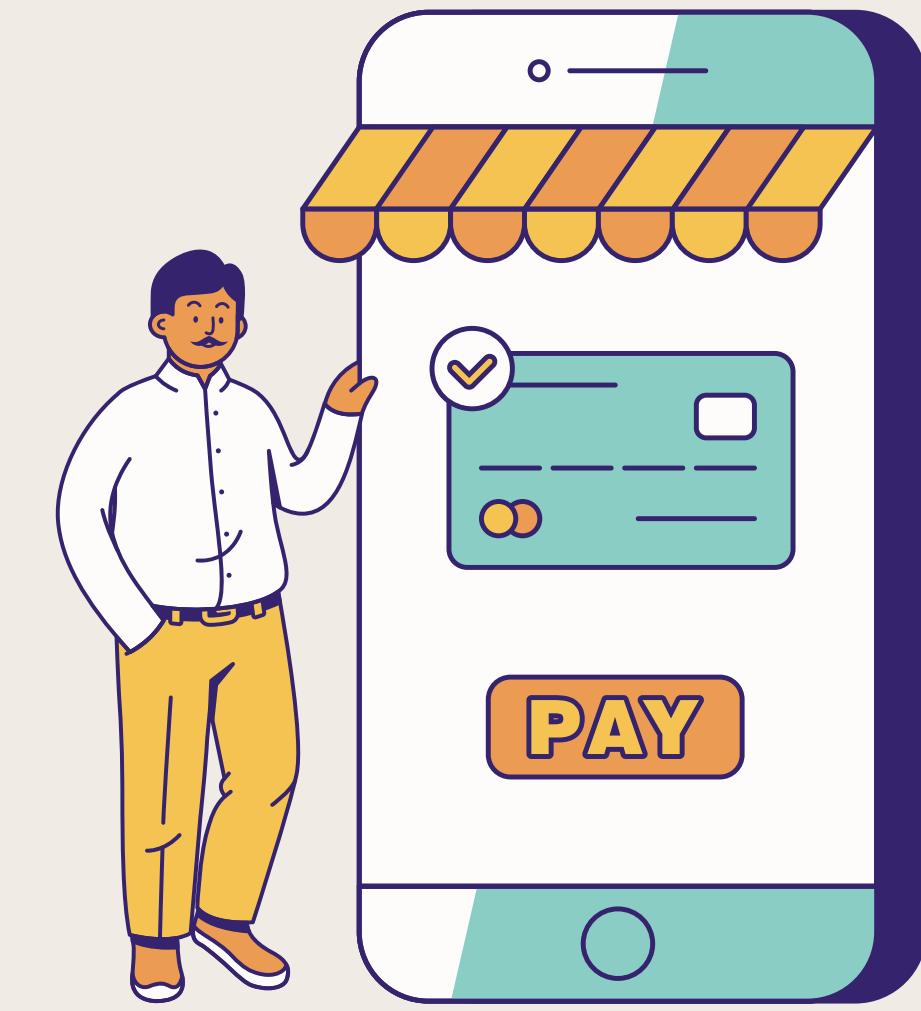
Using Technology to create eco-friendly food packaging

How have social media platforms altered communication

An investigation of Cyber Fraud impact on consumer's behavior to purchase online

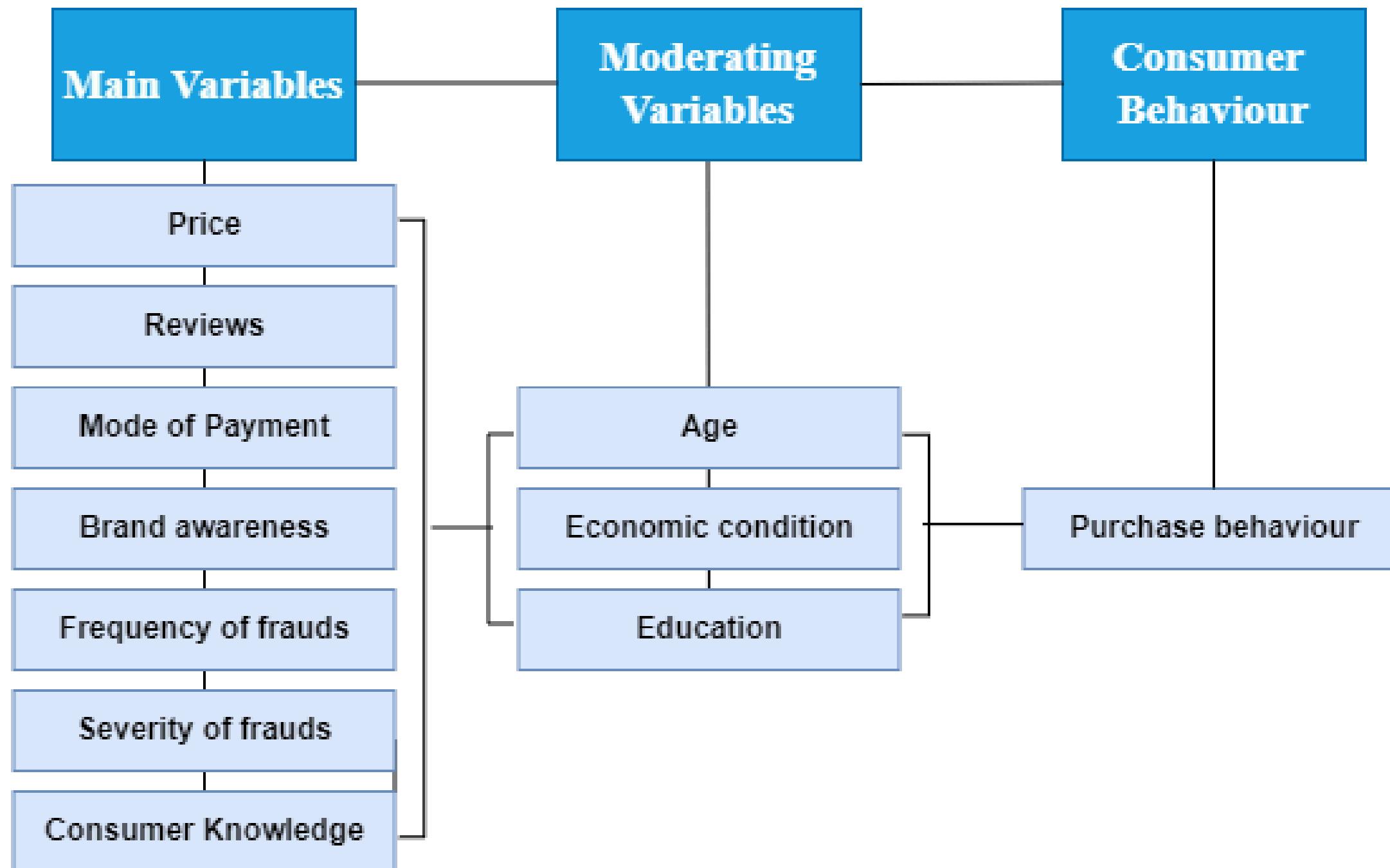
Space-based solar energy: futuristic fantasy or fact

Are facial recognition technologies a threat to privacy or a breakthrough in AI?



## Topic Chosen ✓

An investigation of cyber fraud impact on consumer's behavior to purchase online



- **Price:** Price is a determining factor in consumer decision making. Consumers are often looking for value for money.
- **Reviews:** Online reviews play a key role in building consumer trust. Positive reviews can convince consumers of the legitimacy and reliability of a product or service, while negative reviews can raise a red flag and prevent a purchase
- **Payment method:** Available payment methods can influence consumer behavior, especially when it comes to cyber fraud. Consumers prefer secure payment methods such as credit cards with fraud protection, payment gateways with encryption technology
- **Brand awareness:** It is about how familiar and recognizable your brand is to your target audience.

- **Cyber fraud incidents:** Cyber fraud in online purchases comes in many forms, like phishing scams, fake websites, malware injections, and stolen credit card data.
- **Consumer knowledge:** knowledge levels vary greatly, impacting susceptibility to fraud and overall online shopping behavior.
- **Trust in Institutions:** Institutions such as banks, online retailers, government websites can moderate the likelihood of falling for cyber fraud.
- **Age:** Age can influence how individuals interact with technology and their susceptibility to different types of cyber fraud
- **Economic Conditions:** In times of economic downturn, increased financial pressures may lead to a higher incidence of individuals committing fraud.

# Framed Hypotheses



# Price

- Age has a significant moderating impact on the relationship between Price and the consumers' buying decisions.
- Economic condition has a significant moderating impact on the relationship between Price and the consumers' buying decisions.
- Education has a significant moderating impact on the relationship between Price and consumers' buying decisions.

# Reviews

- Age has a significant moderating impact on the relationship between Reviews and the consumers' buying decisions.
- Economic condition has a significant moderating impact on the relationship between Reviews and the consumers' buying decisions.
- Education has a significant moderating impact on the relationship between Reviews and consumers' buying decisions.

# Mode of payment

- Age has a significant moderating impact on the relationship between Mode of Payment and the consumers' buying decisions.
- Economic condition has a significant moderating impact on the relationship between Mode of Payment and the consumers' buying decisions.
- Education has a significant moderating impact on the relationship between Mode of Payment and consumers' buying decisions.

# Brand awareness

- Age has a significant moderating impact on the relationship between Brand awareness and the consumers' buying decisions.
- Economic condition has a significant moderating impact on the relationship between Brand awareness and the consumers' buying decisions.
- Education has a significant moderating impact on the relationship between Brand awareness and consumers' buying decisions.

# Frequency of frauds

- Age has a significant moderating impact on the relationship between Frequency of frauds and the consumers' buying decisions.
- Economic condition has a significant moderating impact on the relationship between Frequency of frauds and the consumers' buying decisions.
- Education has a significant moderating impact on the relationship between Frequency of frauds and consumers' buying decisions.

## Severity of frauds

- Age has a significant moderating impact on the relationship between Severity of frauds and the consumers' buying decisions.
- Economic condition has a significant moderating impact on the relationship between Severity of frauds and the consumers' buying decisions.
- Education has a significant moderating impact on the relationship between Severity of frauds and consumers' buying decisions.

# Consumer knowledge

- Age has a significant moderating impact on the relationship between Consumer knowledge and the consumers' buying decisions.
- Economic condition has a significant moderating impact on the relationship between Consumer knowledge and the consumers' buying decisions.
- Education has a significant moderating impact on the relationship between Consumer knowledge and consumers' buying decisions.

# **LINKS**

## **Google Form Link:**

<https://forms.gle/pkpNhioHUHWDatveA>

## **Excel File:**

[https://docs.google.com/spreadsheets/d/1UzYznUfHrvjdibpc  
sn2ElnIFHYn1jLOHK4R7dnbJAQE/edit?usp=sharing](https://docs.google.com/spreadsheets/d/1UzYznUfHrvjdibpcsn2ElnIFHYn1jLOHK4R7dnbJAQE/edit?usp=sharing)

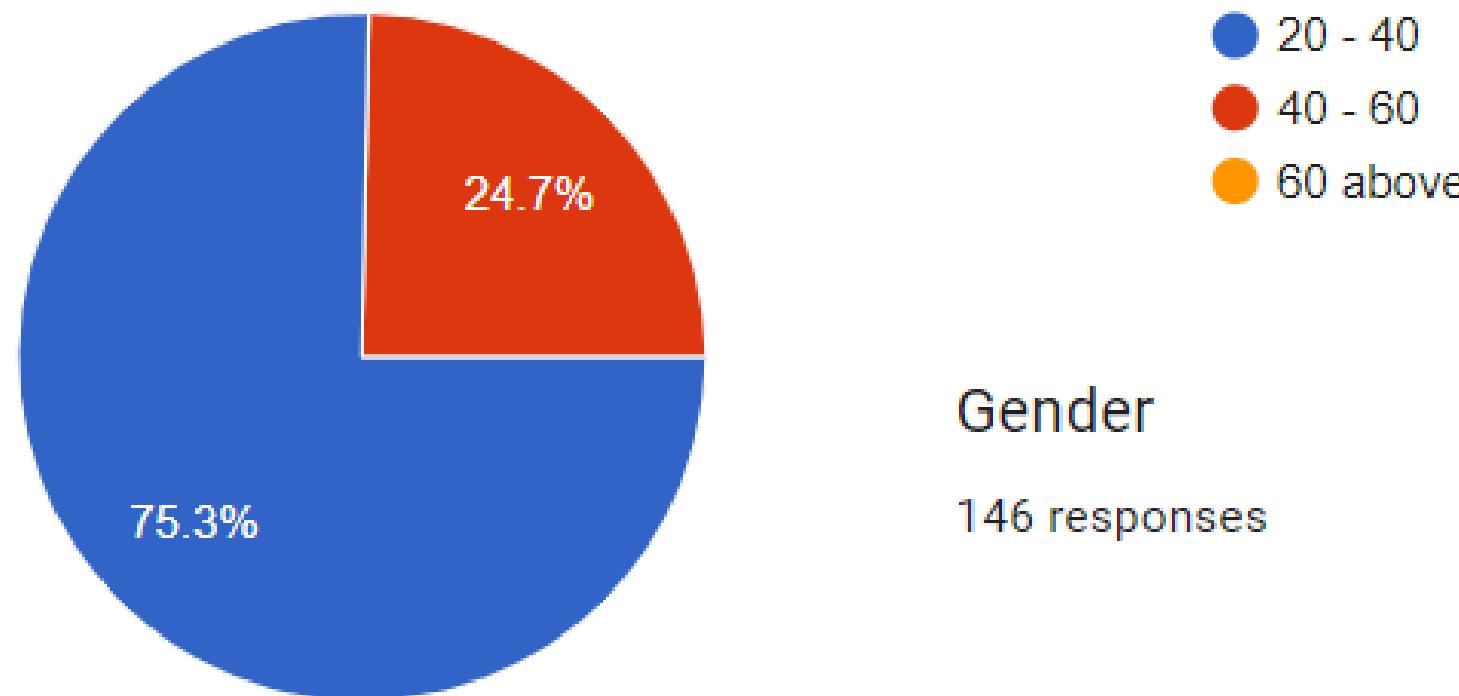
## **Questionnaire**

[https://docs.google.com/document/d/1rmw824MGQ8-  
fufFOcGUfuTYr8nCSlvSos1ZNXNtgDQc/edit](https://docs.google.com/document/d/1rmw824MGQ8-fufFOcGUfuTYr8nCSlvSos1ZNXNtgDQc/edit)

# Distribution based on demographics

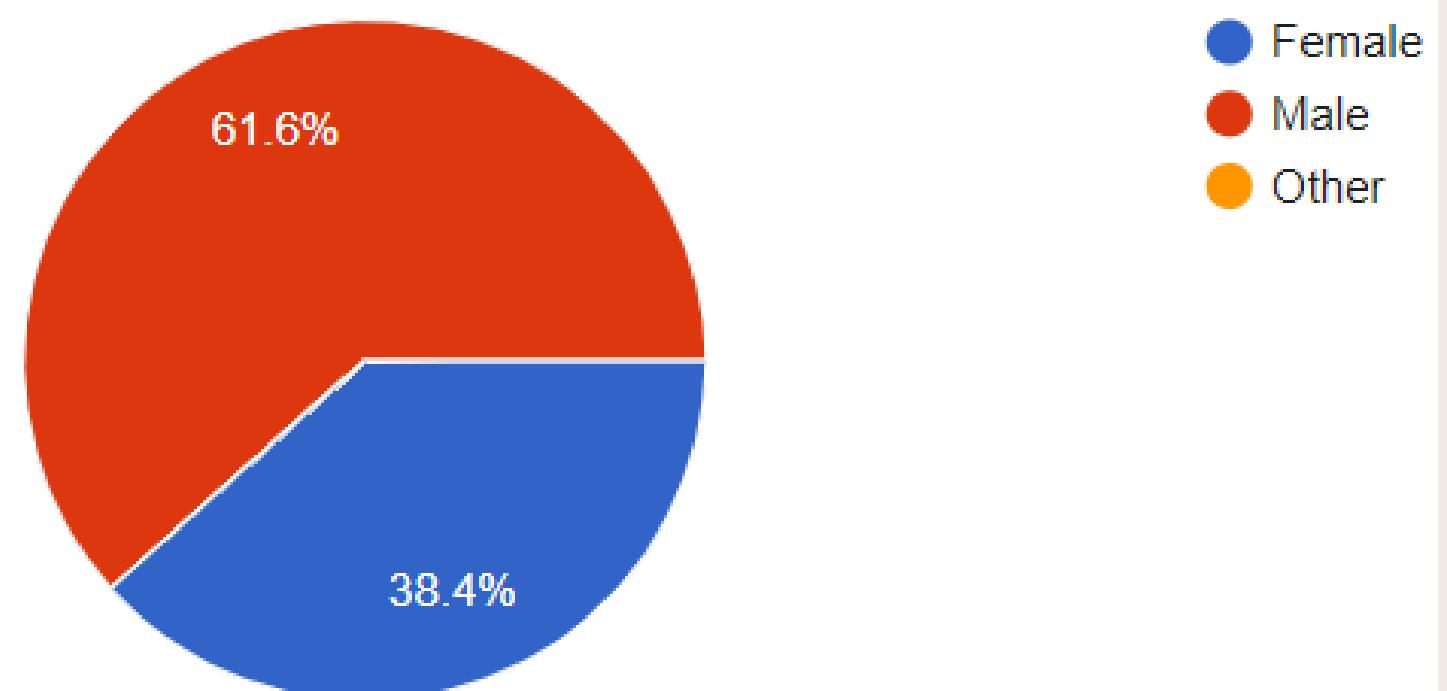
Age

146 responses



Gender

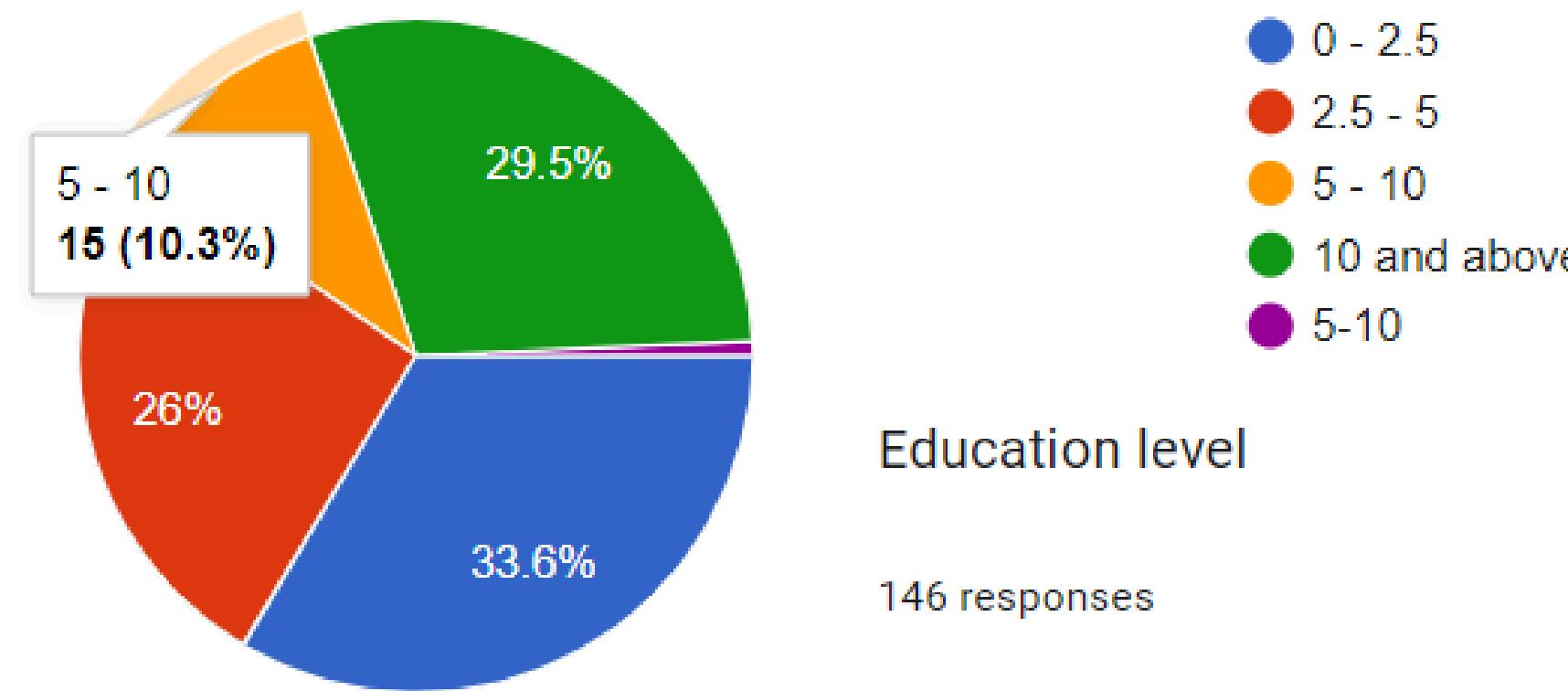
146 responses



# Feedback

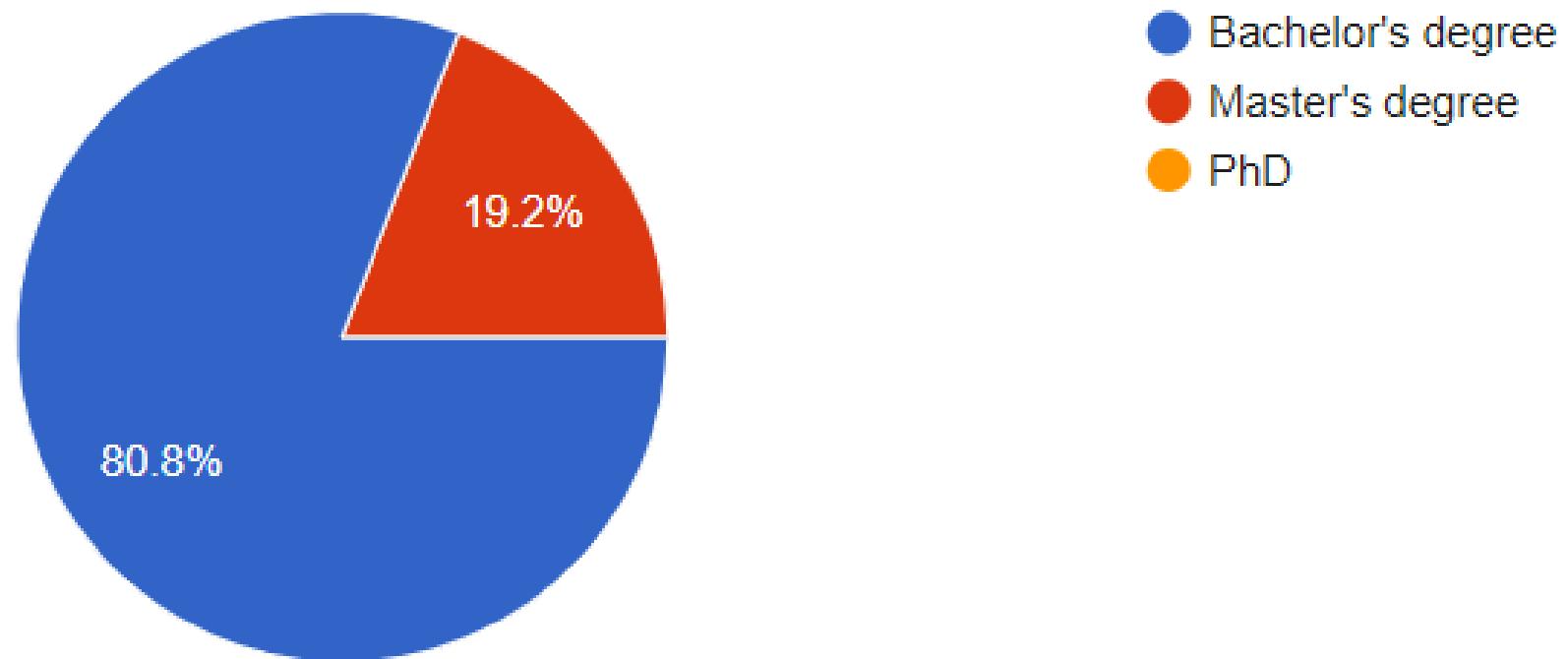
Annual income (In Lakhs)

146 responses



Education level

146 responses

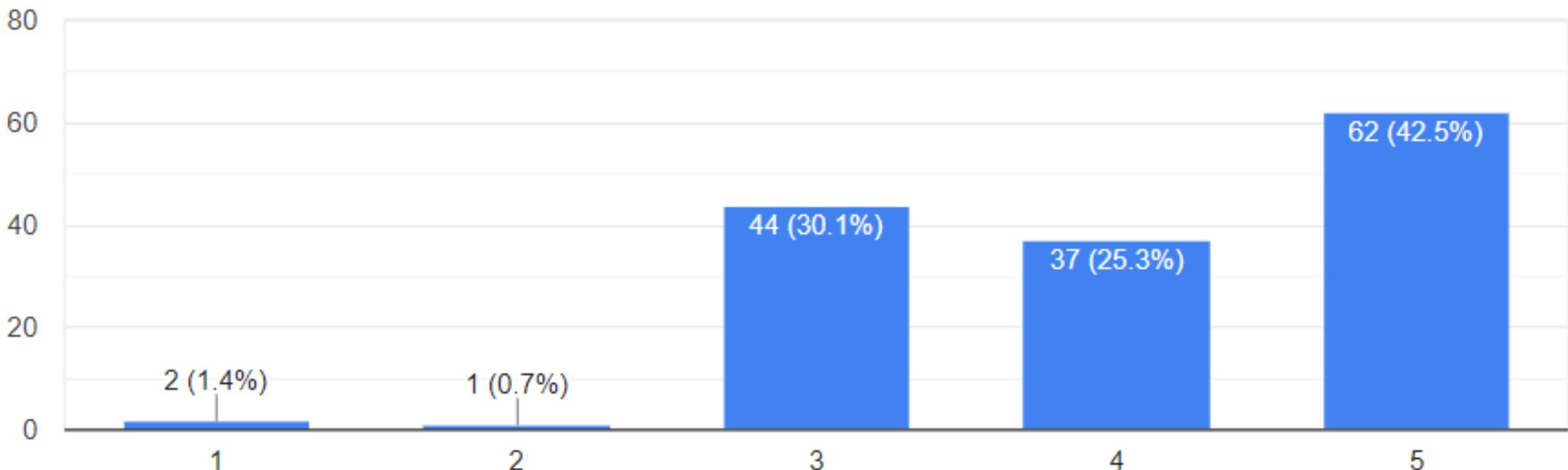


# Feedback

Price plays a pivotal role in online purchase.

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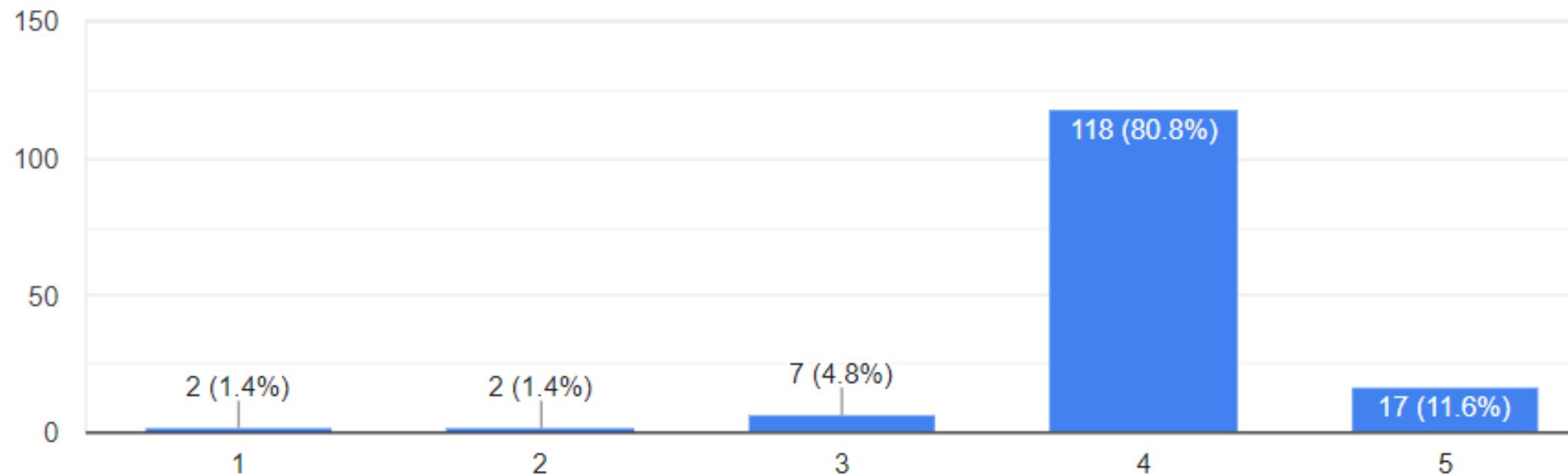
146 responses



People rely on online reviews when considering a product or service for purchase

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146 responses

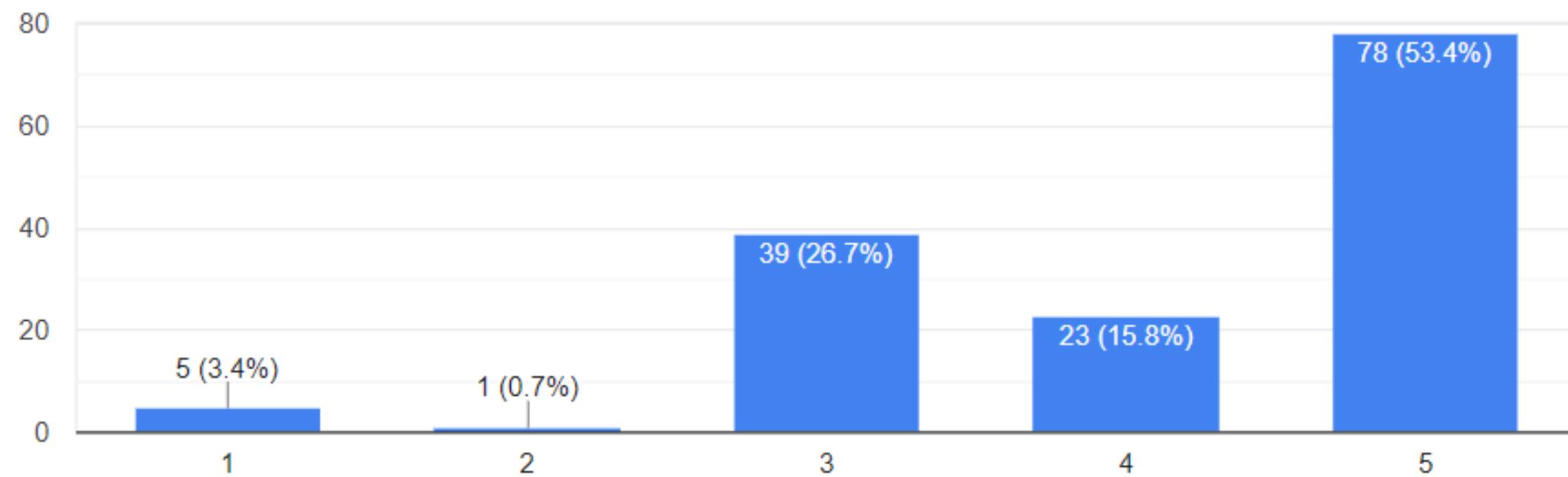


# Feedback

People look for ratings and comments in online reviews to determine the usefulness.

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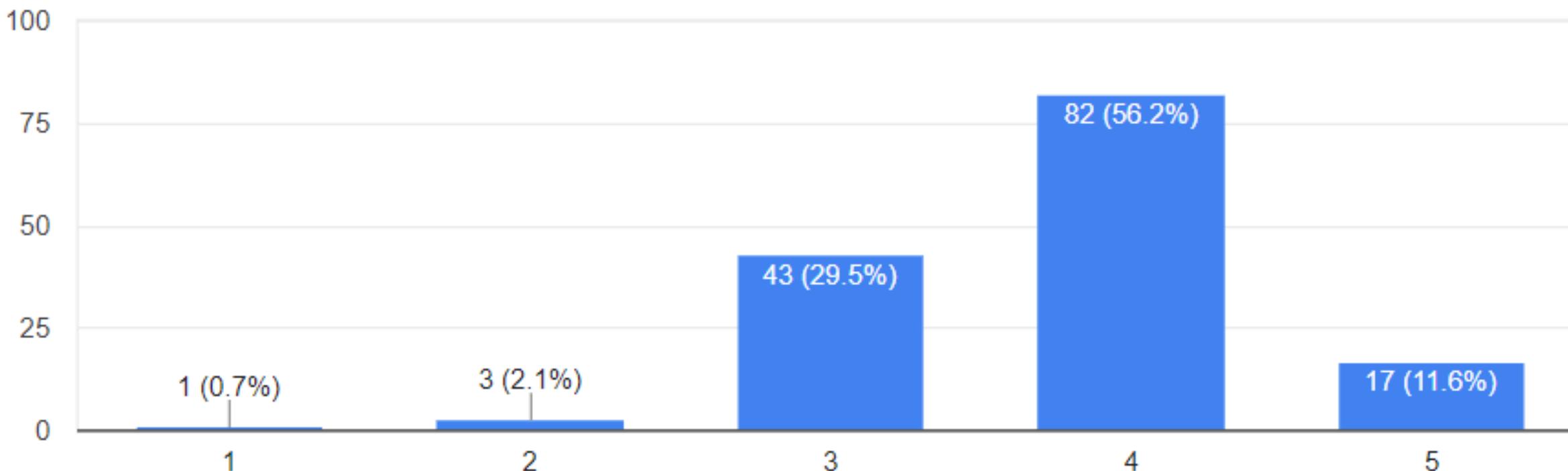
146 responses



Conflicting online reviews make it difficult for people to make a purchase decision.

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146 responses

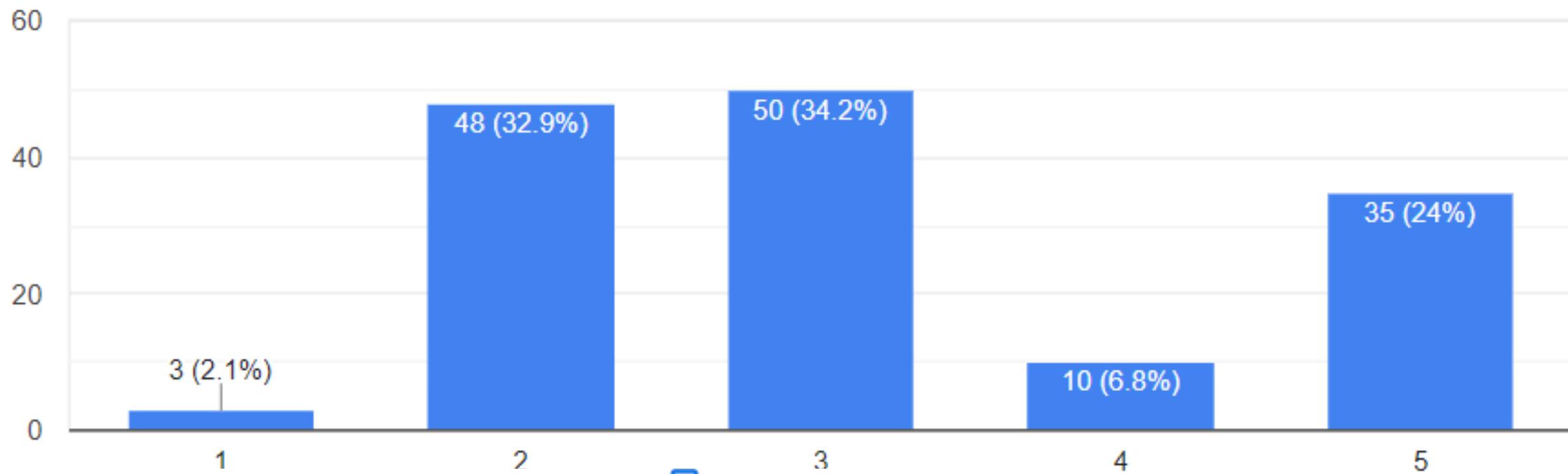


# Feedback

People tend to leave a review after purchasing a product or service online.

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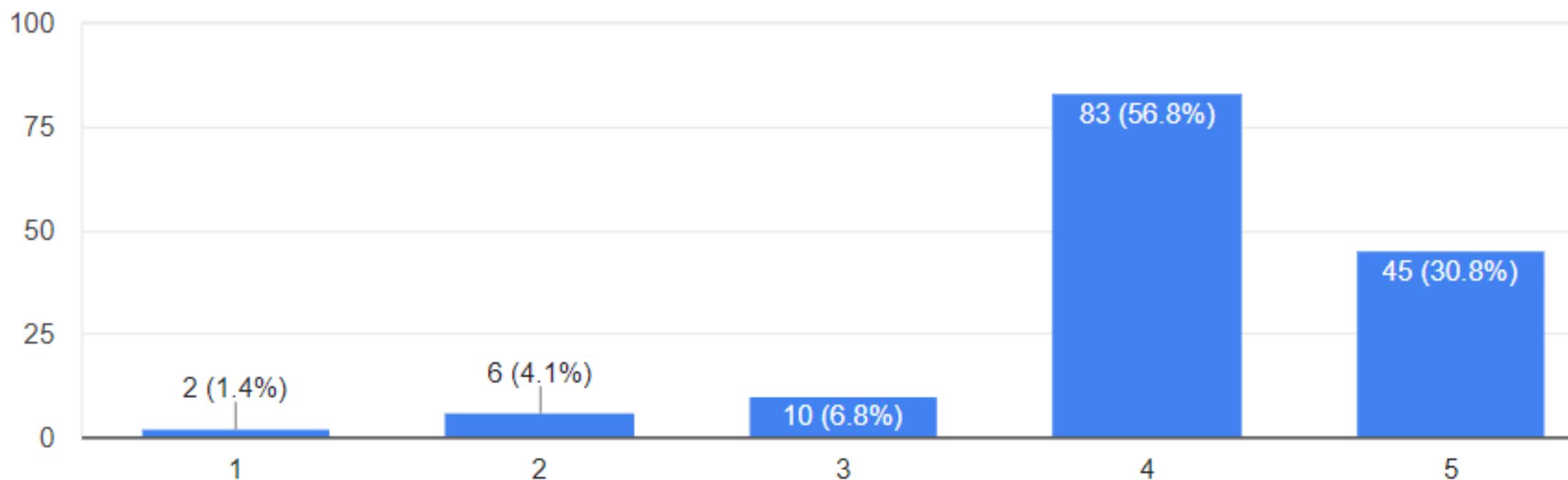
146 responses



OTP is a reliable measure that could be taken to improve the reliability of online reviews.

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146 responses

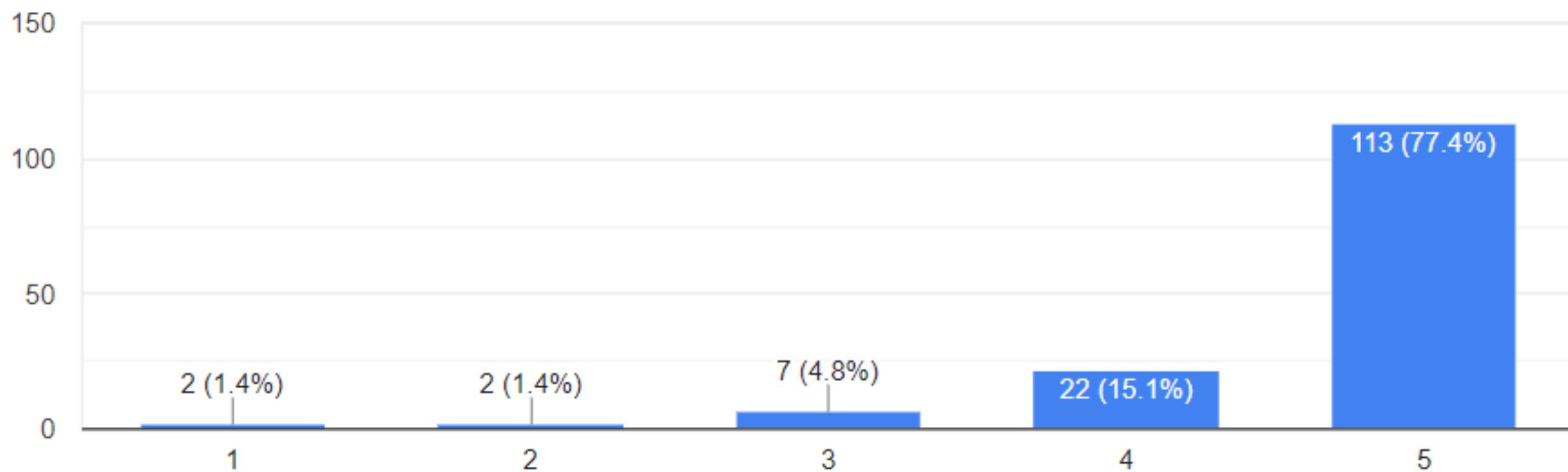


# Feedback

Choice of payment mode influences online purchases.

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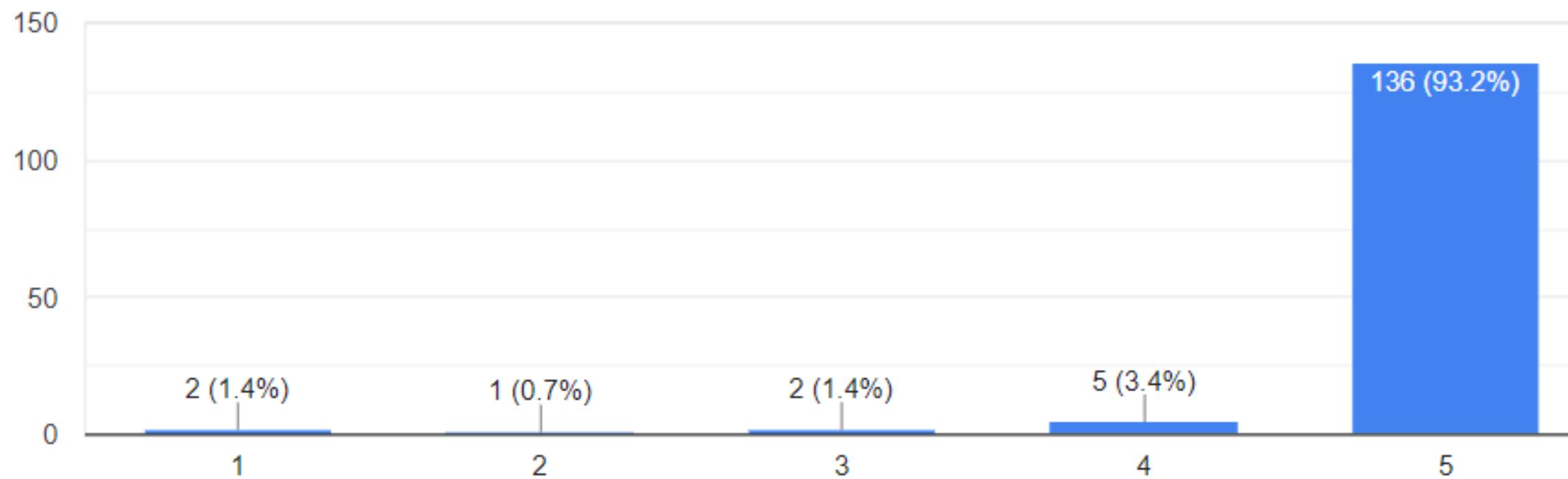
146 responses



Secure payment is highly important .

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146 responses

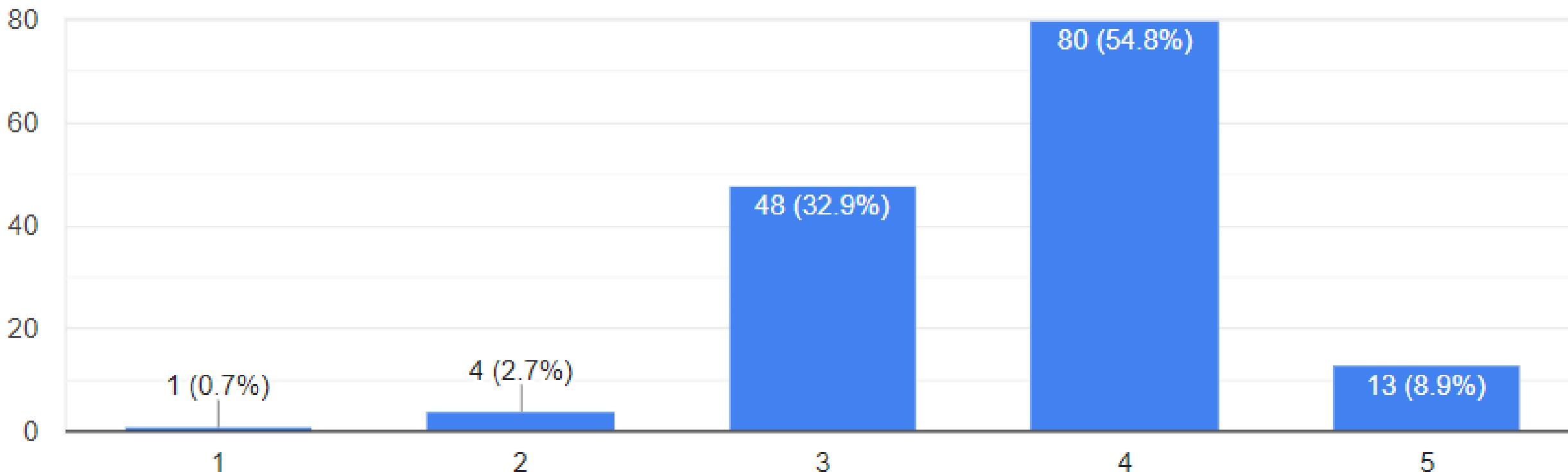


# Feedback

Sometimes people face issues while doing payment for online shopping.

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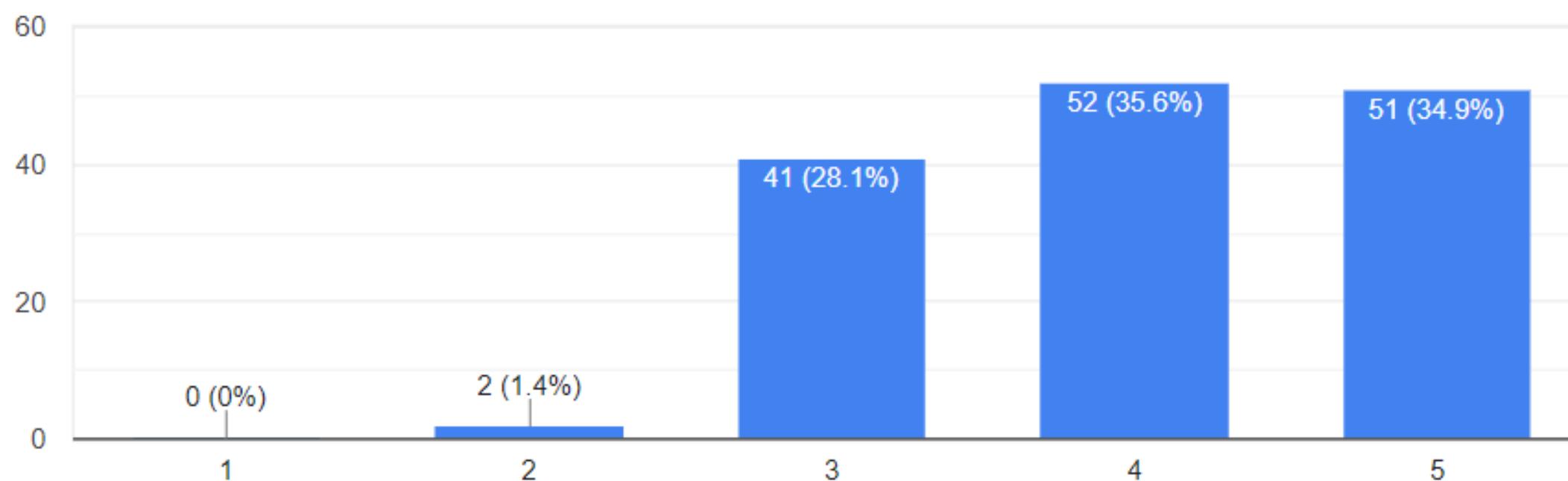
146 responses



People are attracted to alternative payment methods offering any additional rewards & benefits

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146 responses

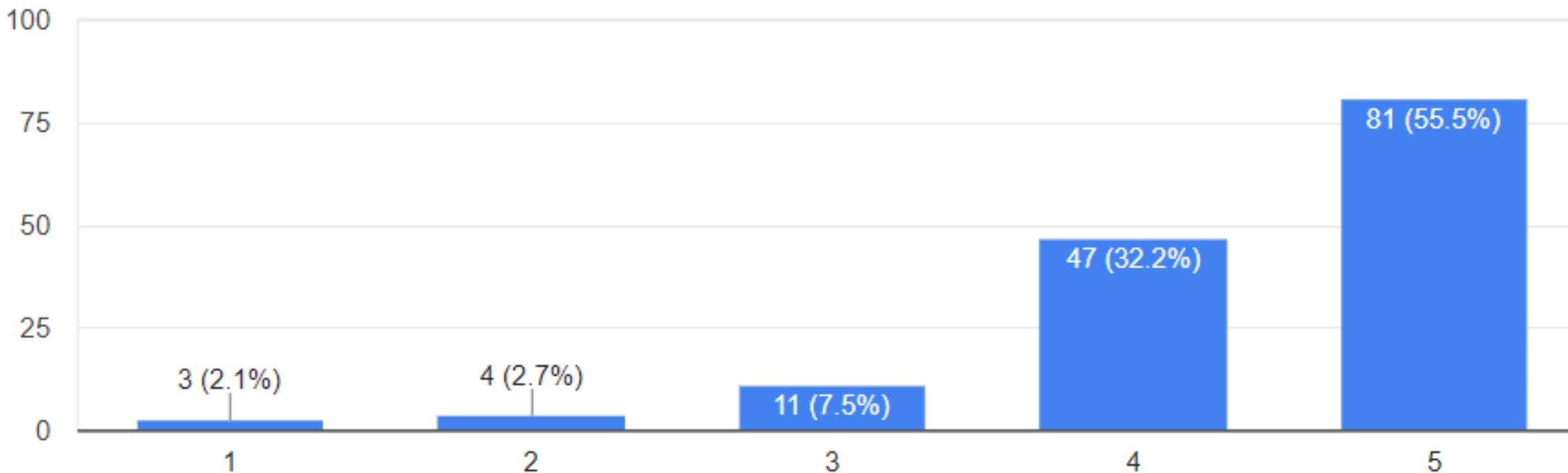


# Feedback

People normally only buy a product online because of its brand name.

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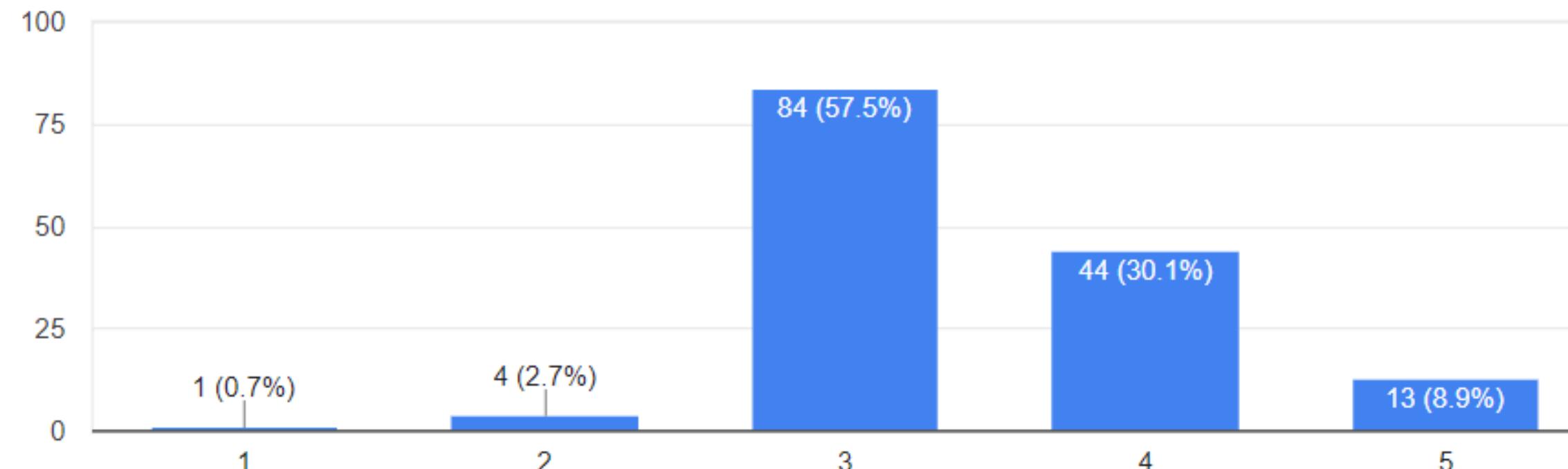
146 responses



People initially trust online shopping are more easily deterred by cyber fraud than those with low trust.

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146 responses

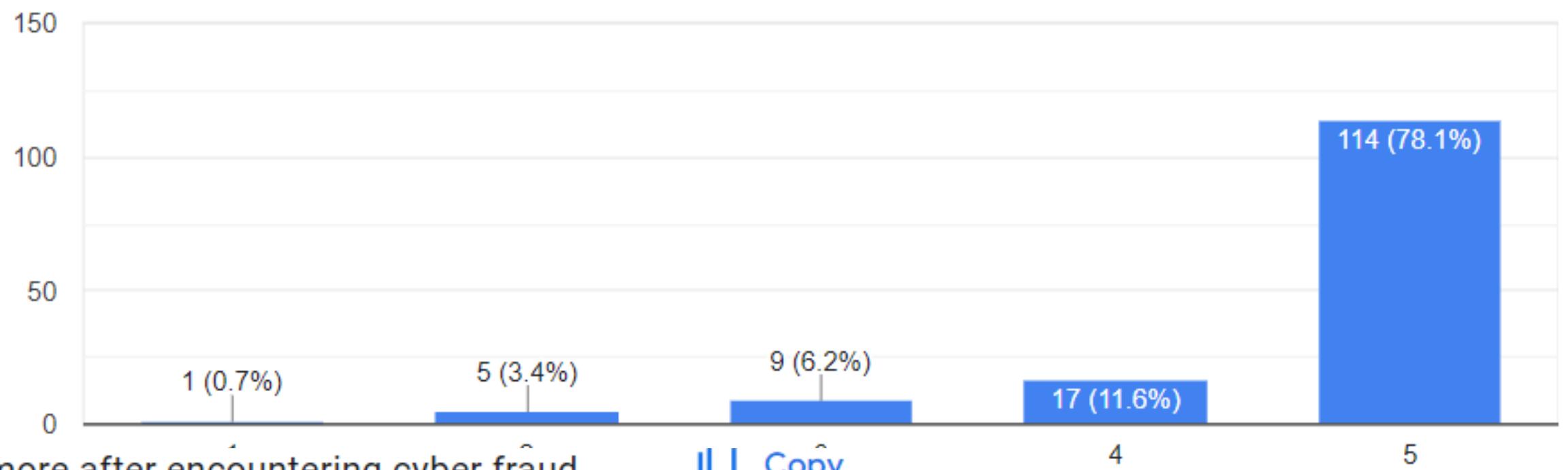


# Feedback

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Consumers who actively learn about cybersecurity practices are less likely to be discouraged by cyber fraud.

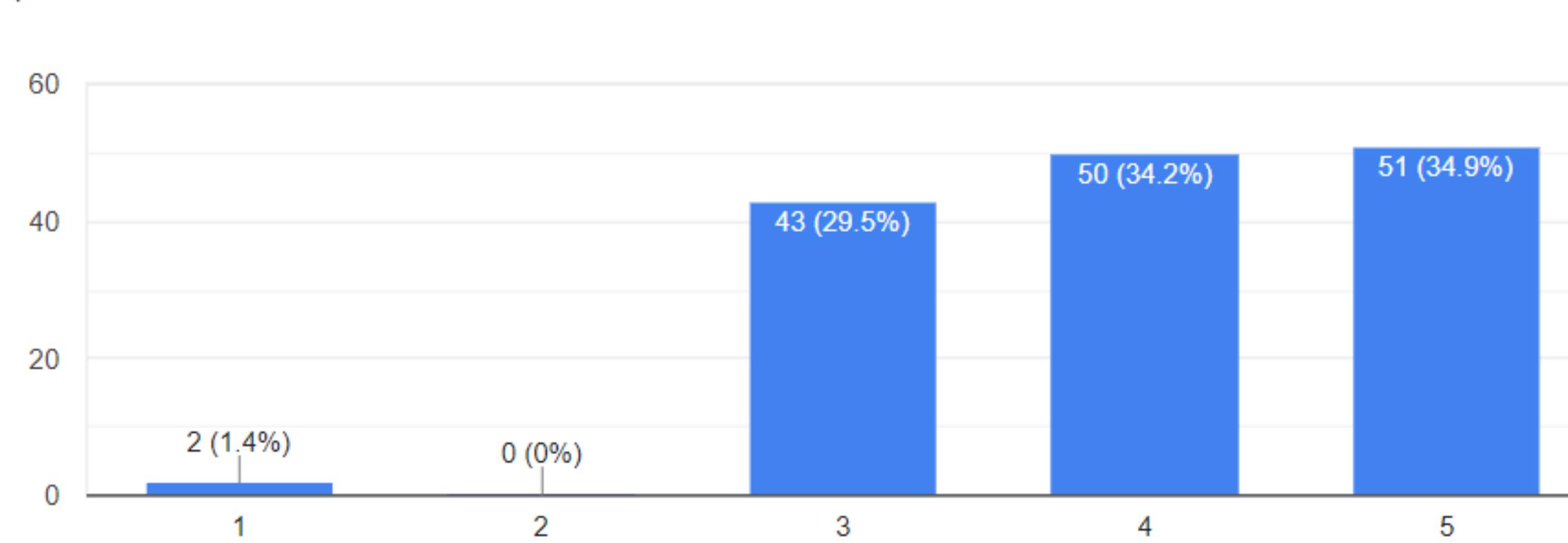
146 responses



Risk-averse consumers avoid online shopping more after encountering cyber fraud.

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146 responses

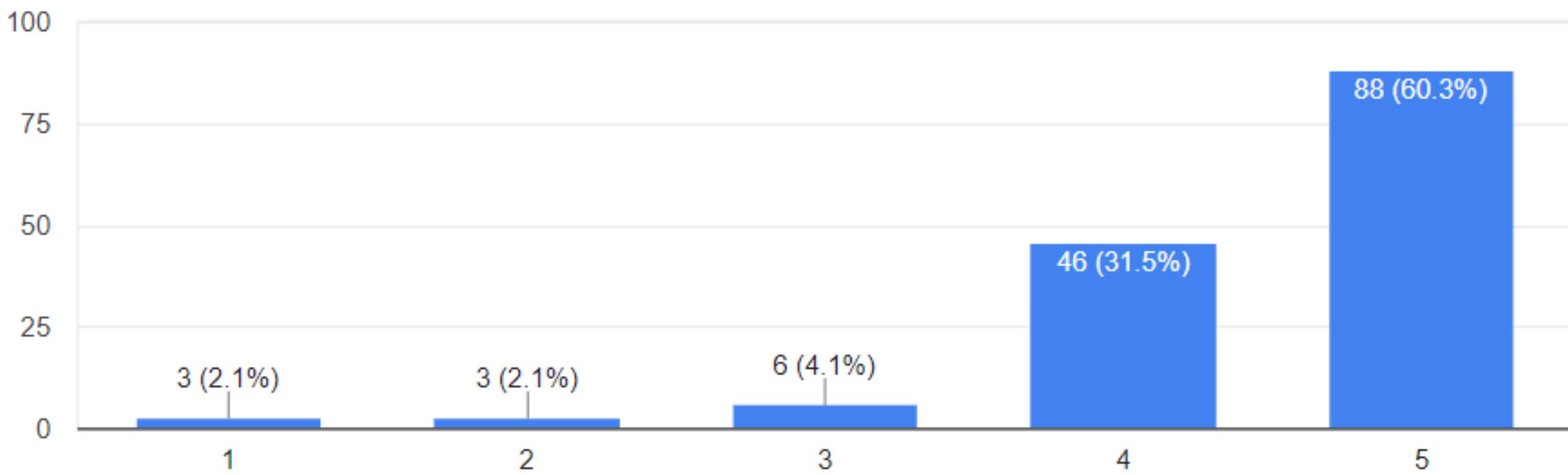


# Feedback

Severe cyber fraud incidents, such as losing money make people afraid to buy things online.

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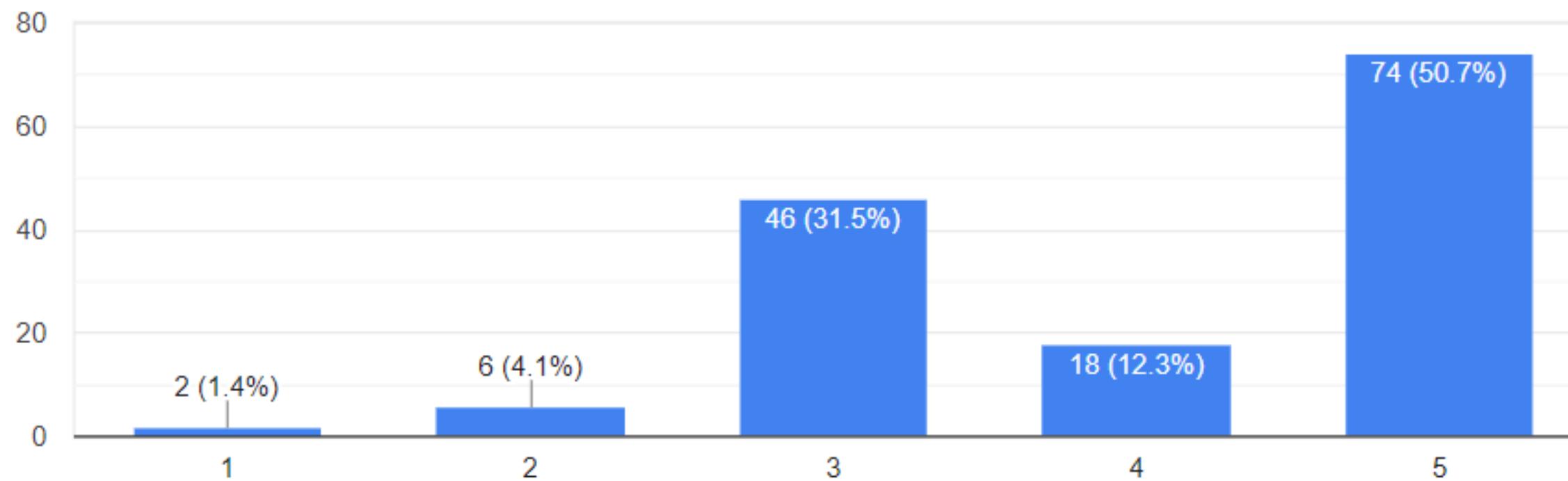
146 responses



People think online fraud is a threat to certain demographics or groups of people.

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146 responses

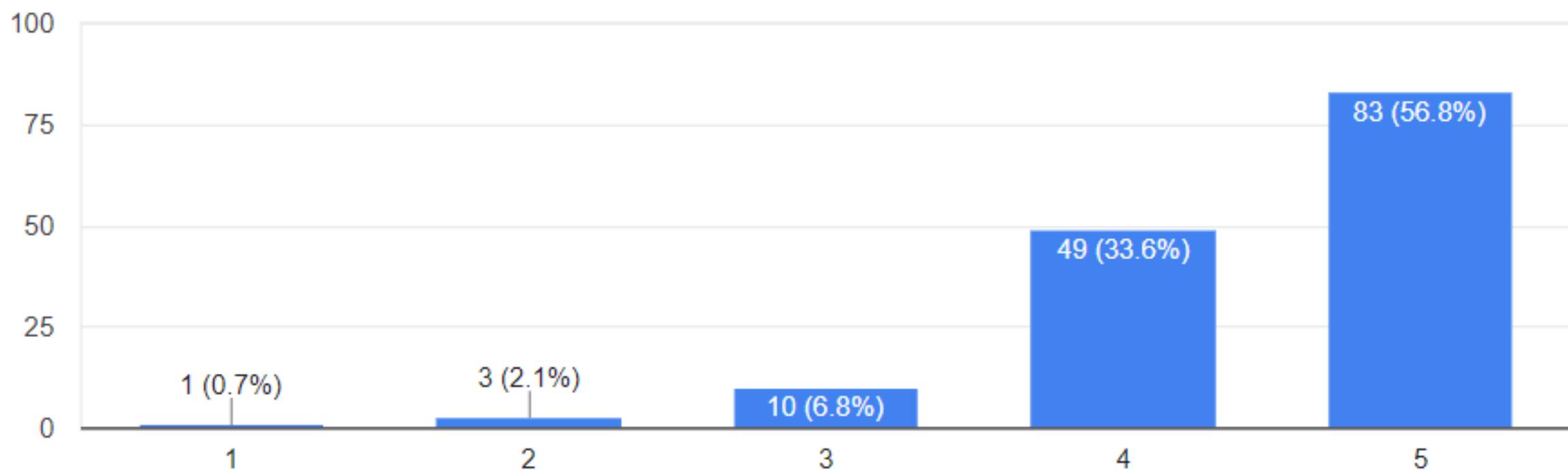


# Feedback

People think authorities should implement measures to reduce severity & impact of online fraud on consumers.

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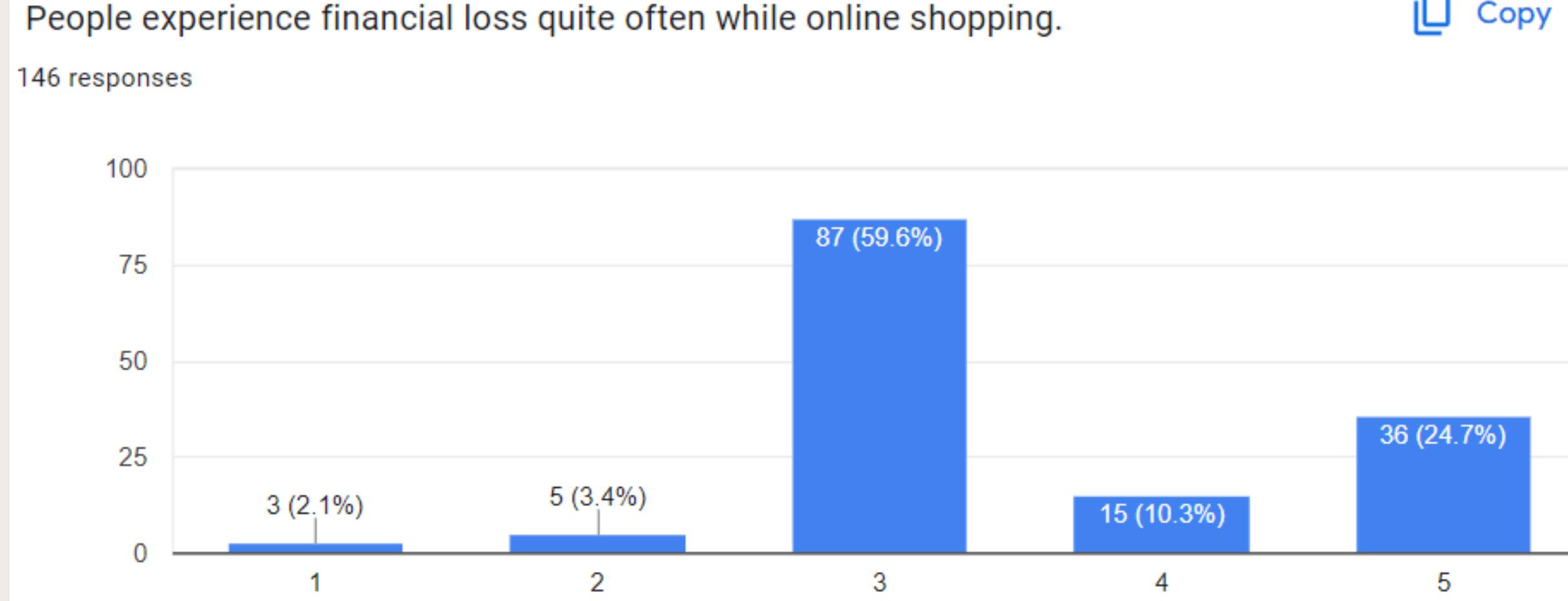
146 responses



People experience financial loss quite often while online shopping.

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146 responses

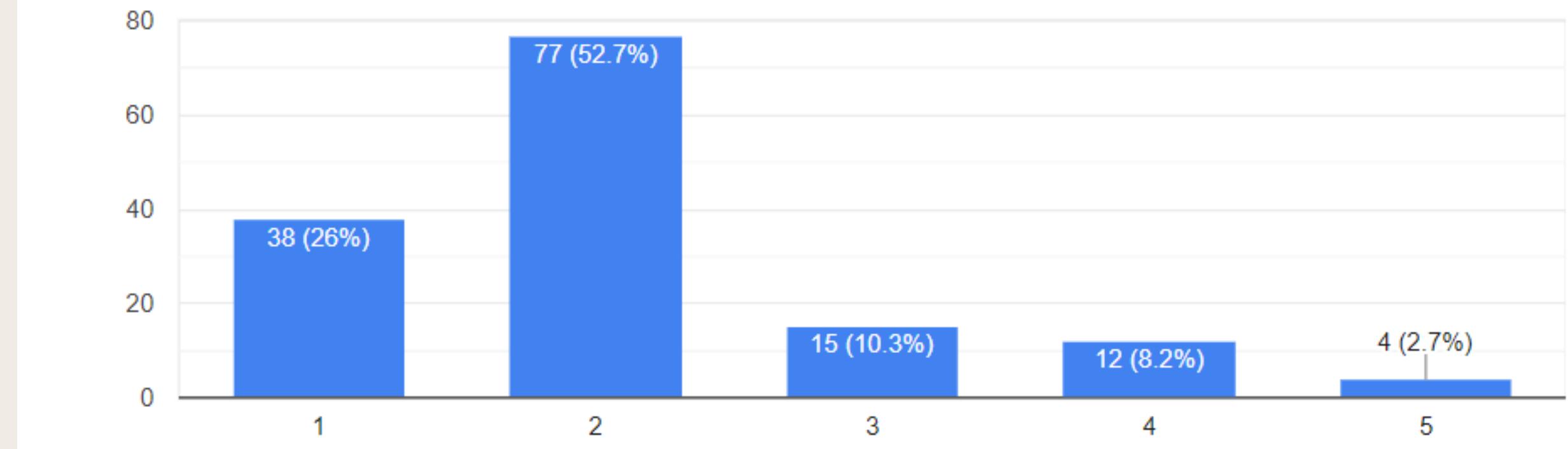


# Feedback

People are interested in participating in educational programs or workshops aimed at improving consumer awareness and knowledge regarding online shopping practices.

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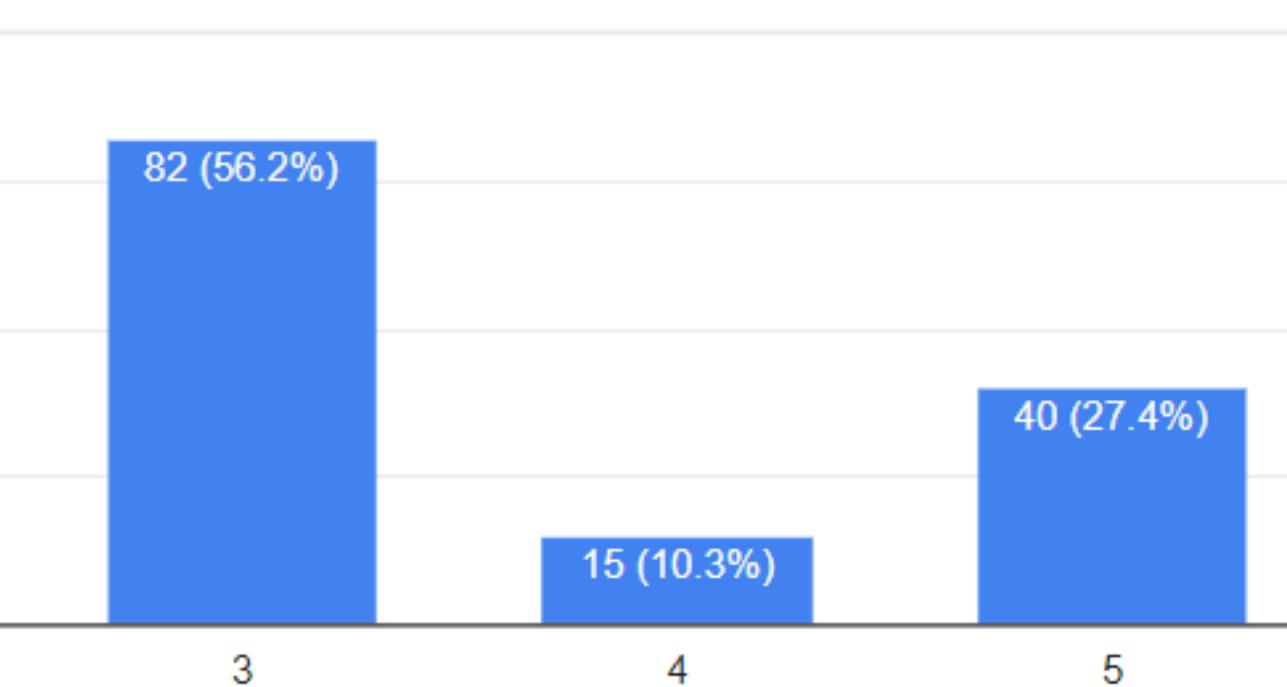
146 responses



People take certain steps to verify the credibility of information or claims presented by online sellers or advertisers.

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146 responses

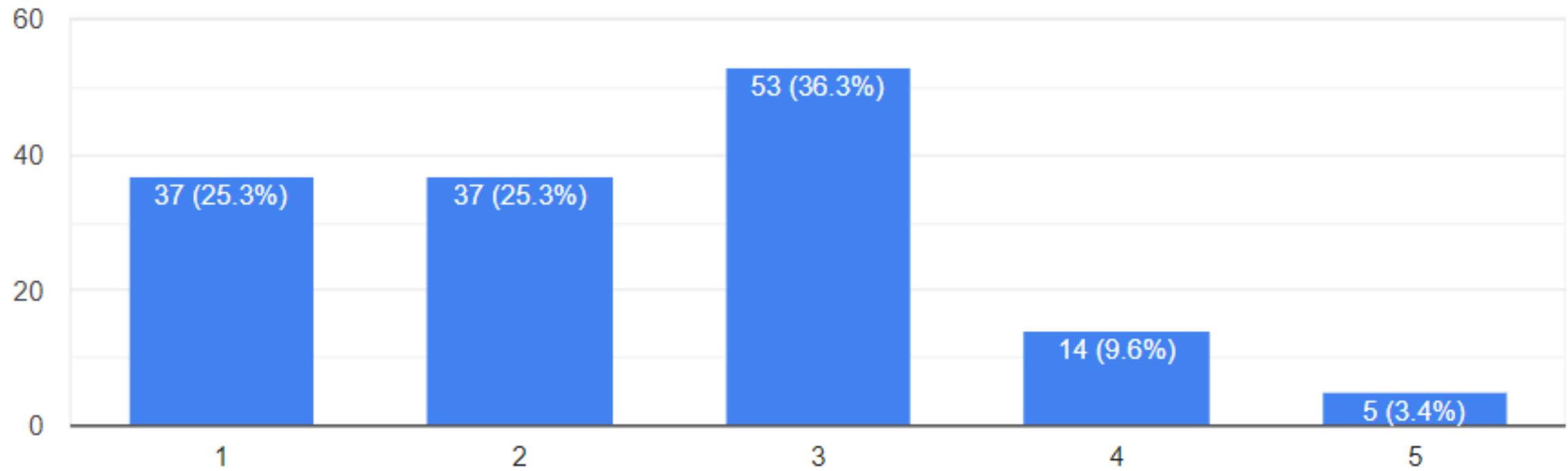


# Feedback

People are likely to report a suspicious activity or fraudulent behavior they saw online.

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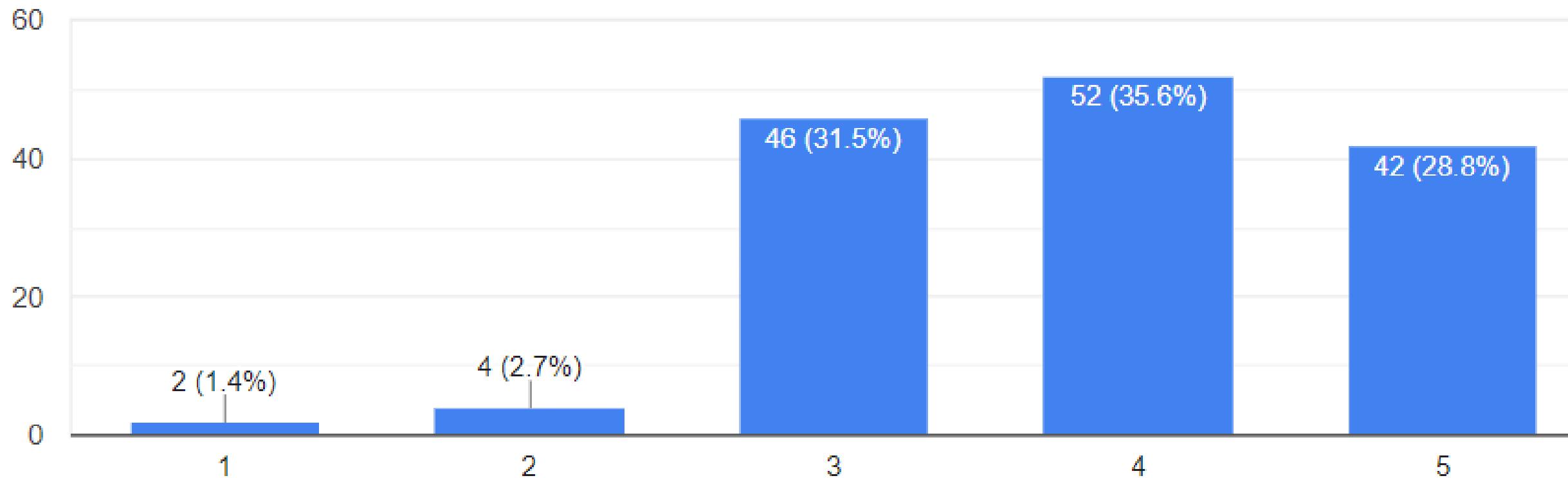
146 responses



Sometimes the online payment service disrupts People's online payment experience.

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146 responses

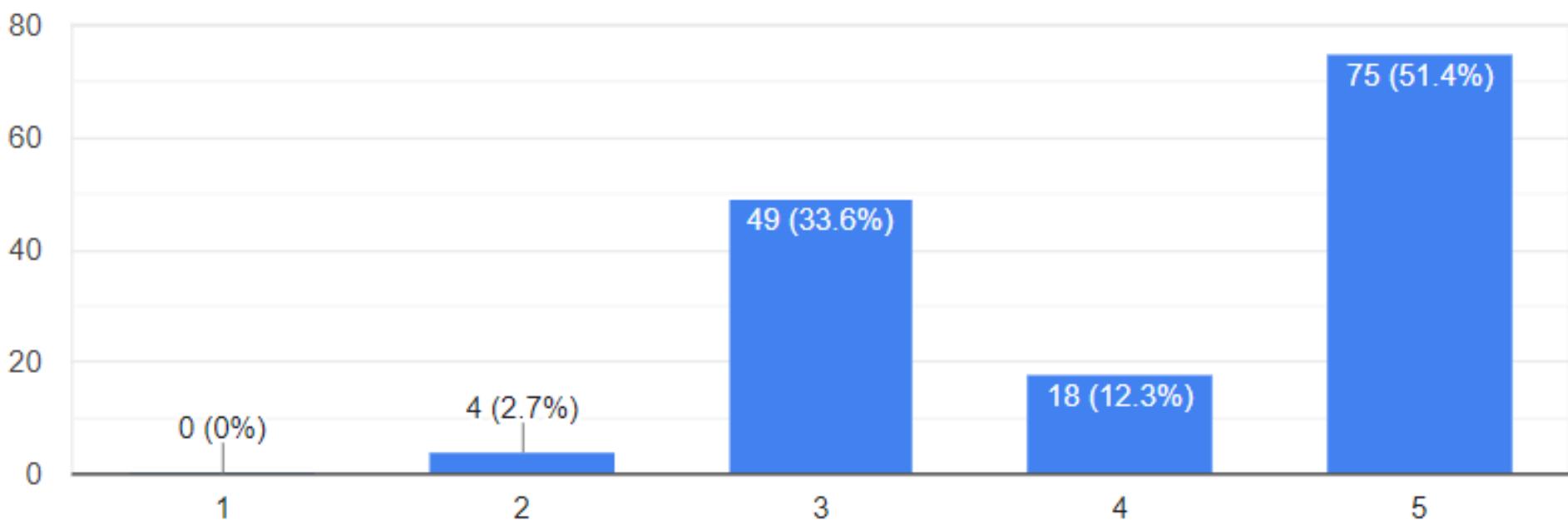


# Feedback

People explore unfamiliar brands that are recommended by friends and family.

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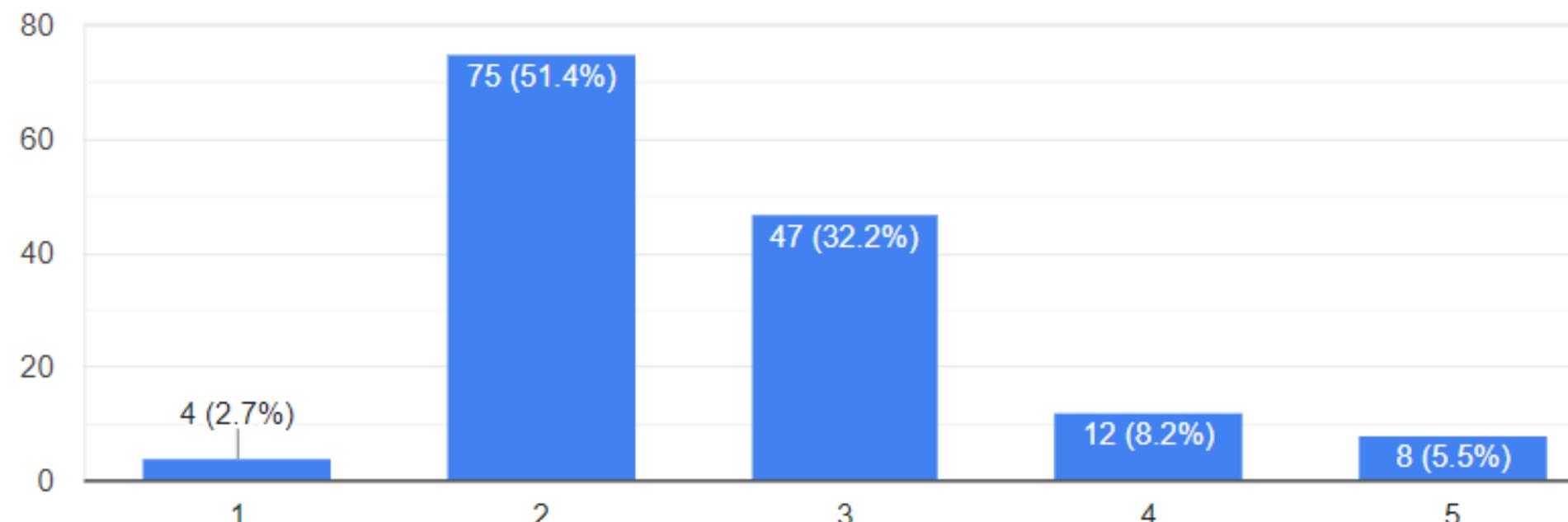
146 responses



Brand loyalty rarely influences online people purchase behavior.

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146 responses

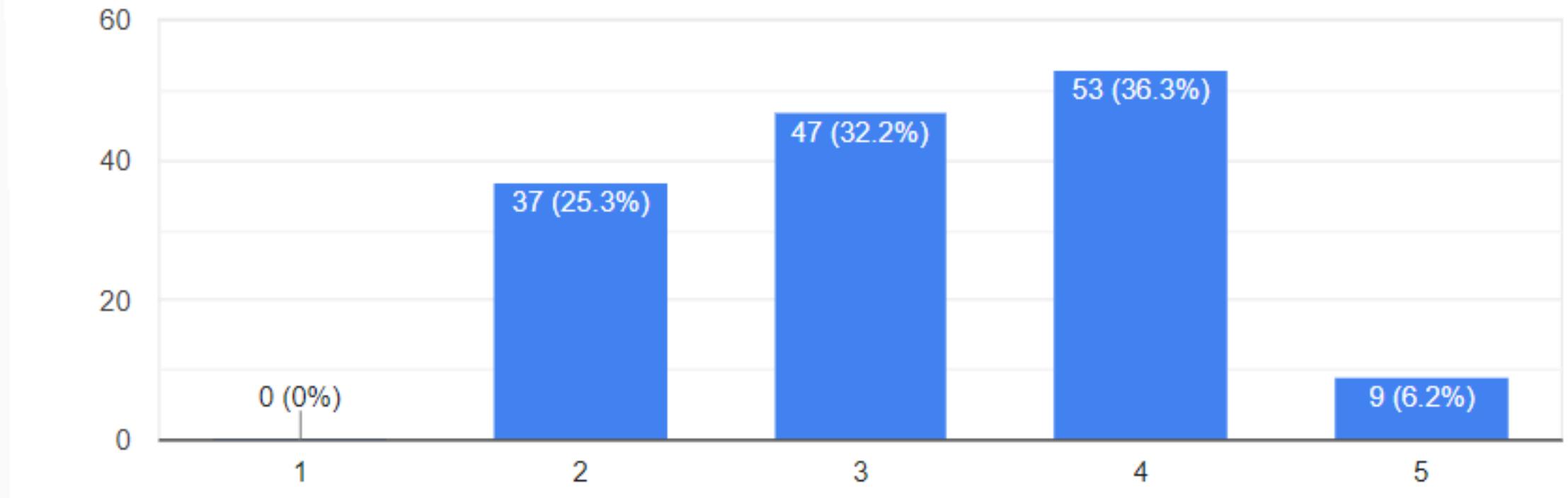


# Feedback

People often encounter ads or emails that they suspect to be fraudulent.

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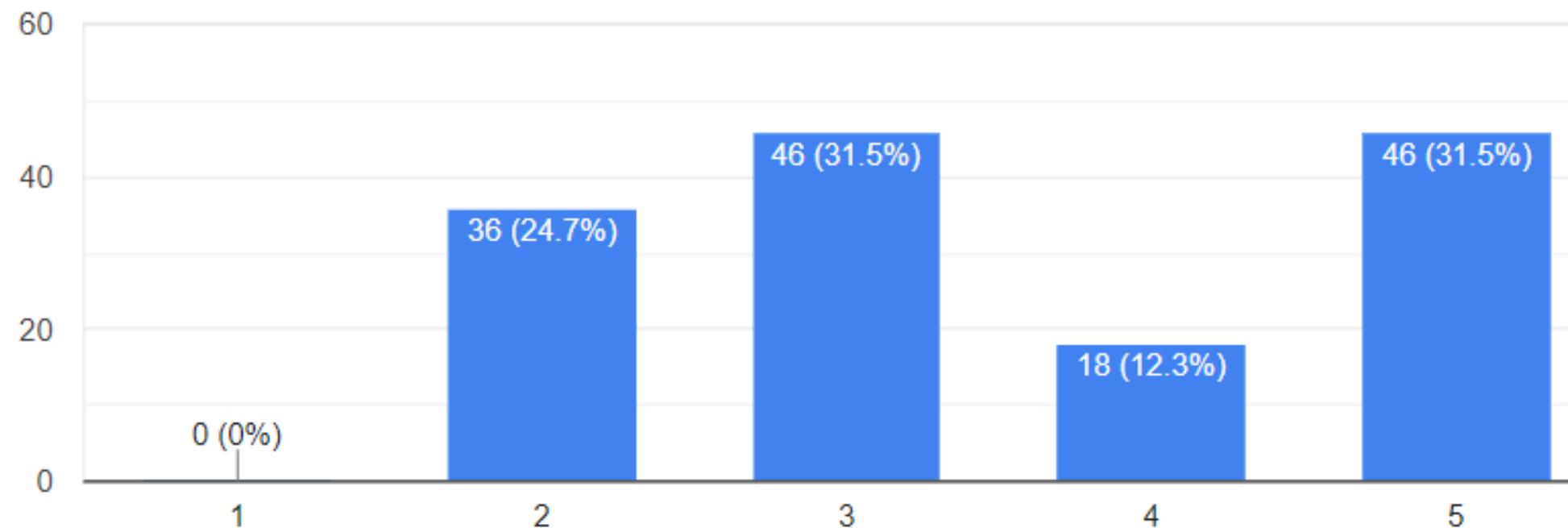
146 responses



Many people fall victim to online scams or fraudulent schemes

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146 responses

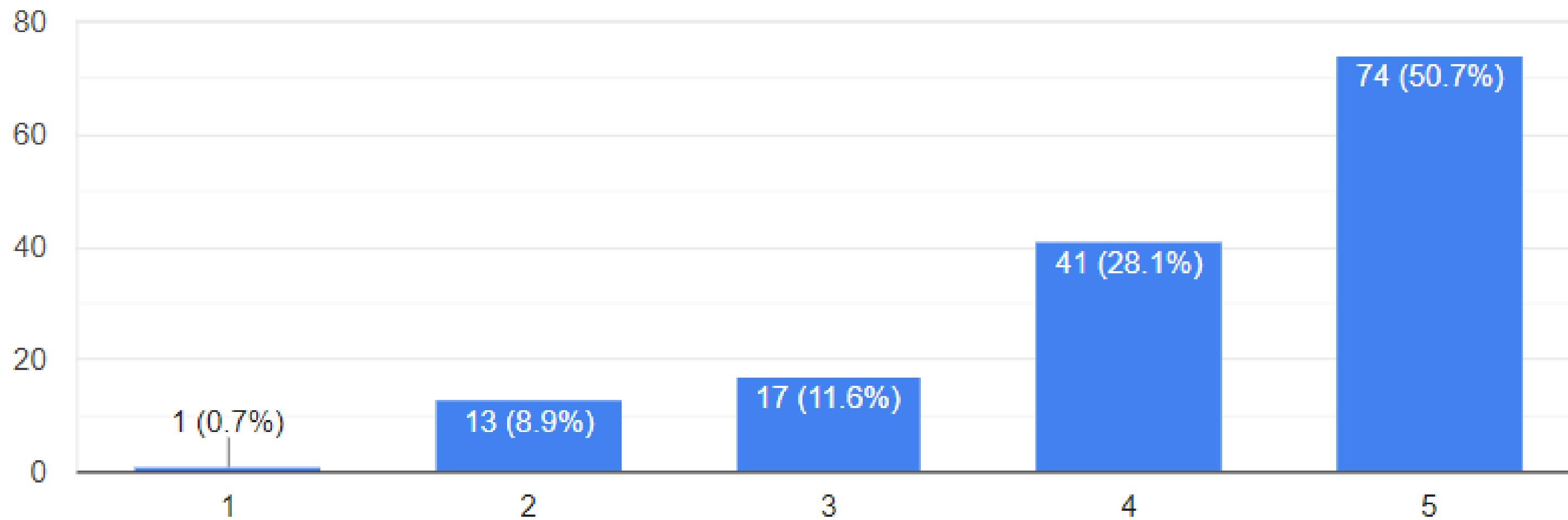


# Feedback

People are confident in their ability to distinguish between fraud and legitimate websites online.

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146 responses



## Screenshots of code

```
install.packages("interactionR")
install.packages("interactions")
library(readxl)
library(caTools)
library(psych)
library(dplyr)
library(interactions)
library(ggplot2)
```

```

getwd()
data = read_xlsx("C:/Users/DELL/Downloads/CyberFraud_part2.xlsx")
# view(data)

#alpha_complete = alpha
#alpha_complete

head(data)

```

```

> getwd()
[1] "C:/Users/DELL/Downloads"
> data = read_xlsx("C:/Users/DELL/Downloads/cyberFraud_part2.xlsx")
> head(data)
# A tibble: 6 × 33
  Timestamp `Email Address` M1   M2   M3   M4   MVP1  MVR1  MVR2  MVR3  MVR4  MVR5  MVMP1
  <dttm>      <chr>     <chr> <chr> <chr> <chr> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
1 2024-04-09 09:51:13 ddeepansh_mba23... 20 - ... Male  10 a... Mast...  3     1     1     3     1     4     1
2 2024-04-09 09:52:46 imahajan_mba23@... 20 - ... Fema... 10 a... Mast...  1     4     1     2     4     2     2
3 2024-04-09 09:59:09 jkaur1_mba23@th... 20 - ... Fema... 10 a... Bach...  1     1     1     4     3     2     1
4 2024-04-10 10:45:47 lubanasingh239@... 20 - ... Male  10 a... Mast...  4     5     5     3     4     4     4
5 2024-04-10 11:01:00 lmalhotra_mba23... 20 - ... Male  10 a... Mast...  5     4     4     3     4     4     4
6 2024-04-10 11:10:15 kjohar_mba23@th... 20 - ... Fema... 0 - ... Bach...  4     3     4     3     3     3     5
# i 20 more variables: MVMP2 <dbl>, MVMP3 <dbl>, MVMP4 <dbl>, MVMP5 <dbl>, MVBA1 <dbl>, MVBA2 <dbl>,
# MVBA3 <dbl>, MVFF1 <dbl>, MVFF2 <dbl>, MVFF3 <dbl>, MVFF4 <dbl>, MVCK1 <dbl>, MVCK2 <dbl>,

```

```
MVR <- data.frame(data[,8:12])
MVR
```

```
> MVR <- data.frame(data[,8:12])
> MVR
```

	MVR1	MVR2	MVR3	MVR4	MVR5
1	1	1	3	1	4
2	4	1	2	4	2
3	1	1	4	3	2
4	5	5	3	4	4
5	4	4	3	4	4
6	3	4	3	3	3
7	2	2	1	4	2
8	5	5	4	1	4
9	4	4	5	4	4
10	4	4	5	3	3
11	3	4	5	1	1

```
###MVR
```

```
MVR <- data.frame(data[,8:12])
```

```
MVR
```

```
alpha_MVR = psych::alpha(MVR, check.keys=TRUE)
```

```
alpha_MVR
```

```
MVR_new <- data.frame(MVR[,-3])
```

```
MVR_new
```

```
alpha_MVR_new = psych::alpha(MVR_new)
```

```
alpha_MVR_new
```

## Main Variable-Review

```
> MVR <- data.frame(data[,8:12])
```

```
> head(MVR)
```

```
  MVR1 MVR2 MVR3 MVR4 MVR5
```

```
1   1   1   3   1   4
```

```
2   4   1   2   4   2
```

```
3   1   1   4   3   2
```

```
4   5   5   3   4   4
```

```
5   4   4   3   4   4
```

```
6   3   4   3   3   3
```

```
> alpha_MVR = psych::alpha(MVR, check.keys=TRUE)
```

```
> alpha_MVR
```

```
Reliability analysis
```

```
Call: psych::alpha(x = MVR, check.keys = TRUE)
```

raw_alpha	std.alpha	G6(smc)	average_r	s/N	ase	mean	sd	median_r
0.43	0.45	0.61	0.14	0.83	0.07	3.8	0.5	0.18

Reliability if an item is dropped:

	raw_alpha	std.alpha	G6(smc)	average_r	s/N	alpha	se	var.r	med.r
MVR1	0.32	0.263	0.52	0.082	0.357	0.085	0.126	0.077	
MVR2	-0.17	0.058	0.23	0.015	0.062	0.163	0.077	0.081	
MVR3	0.56	0.572	0.62	0.251	1.338	0.055	0.050	0.319	
MVR4	0.55	0.567	0.55	0.247	1.310	0.057	0.025	0.242	
MVR5	0.34	0.350	0.54	0.118	0.537	0.082	0.127	0.148	

## Main variable - Mode of Payment

```
> MVMP <- data.frame(data[,13:17])
> head(MVMP)
  MVMP1 MVMP2 MVMP3 MVMP4 MVMP5
1     1     1     1     3     1
2     2     3     3     4     2
3     1     1     3     2     1
4     4     5     4     4     4
5     4     4     3     3     3
6     5     5     5     4     5
> alpha_MVMP = psych::alpha(MVMP)
> alpha_MVMP

Reliability analysis
Call: psych::alpha(x = MVMP)

  raw_alpha std.alpha G6(smc) average_r S/N    ase mean    sd median_r
0.65        0.68      0.75       0.3 2.1 0.048  4.2 0.49      0.28
```

# Main Variable - Brand Awareness

```
> MVBA <- data.frame(data[,18:20])
> head(MVBA)
  MVBA1 MVBA2 MVBA3
1     1     3     1
2     3     2     2
3     1     2     5
4     4     4     4
5     4     4     3
6     4     4     2
> alpha_MVBA = psych::alpha(MVBA)
> alpha_MVBA

Reliability analysis
call: psych::alpha(x = MVBA)

  raw_alpha std.alpha G6(smc) average_r S/N    ase   mean      sd median_r
0.48       0.47     0.51      0.23 0.9 0.075  3.7 0.64  0.026

  95% confidence boundaries
    lower alpha upper
Feldt     0.32   0.48   0.61
Duhachek  0.34   0.48   0.63

Reliability if an item is dropped:
  raw_alpha std.alpha G6(smc) average_r   S/N alpha se var.r med.r
MVBA1      0.043     0.043    0.022     0.022 0.045   0.158   NA 0.022
MVBA2      0.050     0.050    0.026     0.026 0.053   0.157   NA 0.026
MVBA3      0.782     0.784    0.645     0.645 3.635   0.036   NA 0.645
```

## Main Variable - Brand Awareness

```
> MVBA_new <- data.frame(MVBA[,-3])
> head(MVBA_new)
  MVBA1 MVBA2
1      1     3
2      3     2
3      1     2
4      4     4
5      4     4
6      4     4
> alpha_MVBA = psych::alpha(MVBA_new) #here we increased alpha value
> alpha_MVBA

Reliability analysis
Call: psych::alpha(x = MVBA_new)

  raw_alpha std.alpha G6(smc) average_r s/N    ase mean     sd median_r
        0.78       0.78     0.65       0.65  3.6 0.036  4.2  0.85     0.65
```

# Main Variable - Frequency of Frauds

```
> MVFF <- data.frame(data[,21:24])
> head(MVFF)
  MVFF1 MVFF2 MVFF3 MVFF4
1     4     4     5     3
2     3     4     4     3
3     4     3     2     1
4     4     4     4     4
5     4     4     4     4
6     4     5     5     3
> # ?alpha()
> alpha_MVFF = psych::alpha(MVFF,check.keys=TRUE)
Warning message:
In psych::alpha(MVFF, check.keys = TRUE) :
  Some items were negatively correlated with the first principal component
  and were logically reversed.
  This is indicated by a negative sign for the variable name.
> alpha_MVFF

Reliability analysis
Call: psych::alpha(x = MVFF, check.keys = TRUE)

  raw_alpha std.alpha G6(smc) average_r   S/N    ase mean      sd median_r
        0.81       0.16      0.54      0.045 0.19 0.026  2.7 0.83      0.052
```

## Main Variable - Consumer Knowledge

```
> MVCK <- data.frame(data[,25:26])
> head(MVCK)
  MVCK1 MVCK2
1      1      3
2      3      3
3      4      2
4      4      3
5      3      4
6      5      5
> alpha_MVCK = psych::alpha(MVCK)
> alpha_MVCK

Reliability analysis
Call: psych::alpha(x = MVCK)

  raw_alpha std.alpha G6(smc) average_r   S/N    ase   mean     sd median_r
0.15        0.15    0.083      0.083 0.18 0.14  2.8  0.72    0.083
```

# Main Variable - Severity of Frauds

```
> MVSF <- data.frame(data[,27:29])
> head(MVSF)
  MVSF1 MVSF2 MVSF3
1     3     1     3
2     3     4     4
3     2     3     2
4     4     3     4
5     4     4     3
6     3     4     5
> alpha_MVSF = psych::alpha(MVSF)
Some items ( MVSF3 ) were negatively correlated with the first principal component
probably should be reversed.
To do this, run the function again with the 'check.keys=TRUE' option
In psych::alpha(MVSF) :
  Some items were negatively correlated with the first principal component and
should be reversed.
To do this, run the function again with the 'check.keys=TRUE' option
> alpha_MVSF

Reliability analysis
call: psych::alpha(x = MVSF)

  raw_alpha std.alpha G6(smc) average_r   S/N    ase   mean      sd median_r
        0.13       0.037      0.18      0.012 0.038 0.11      4 0.57    0.0052
```

## Main Variable - Purchase Behavior

```
> ##OVPB
> OVPB <- data.frame(data[,30:33])
> head(OVPB)
  OVPB1 OVPB2 OVPB3 OVPB4
1     1     1     3     3
2     4     4     2     2
3     2     1     2     2
4     4     4     4     4
5     4     4     4     4
6     5     4     5     5
> alpha_OVPB = psych::alpha(OVPB)
> alpha_OVPB

Reliability analysis
Call: psych::alpha(x = OVPB)

  raw_alpha std.alpha G6(smc) average_r   S/N      ase    mean      sd median_r
        0.49       0.49       0.5       0.19  0.95  0.068     4.1    0.51      0.14
```

```
# M1 = Age  
M1 <- data.frame(data[,3])  
M1
```

```
> M1 <- data.frame(data[,3])  
> M1
```

```
      M1  
1 20 - 40  
2 20 - 40  
3 20 - 40  
4 20 - 40  
5 20 - 40  
6 20 - 40  
7 20 - 40  
8 20 - 40  
9 20 - 40
```

```
M1_data = M1%>%mutate(M1 = recode(M1, '20 - 40'= 0,'40 - 60'= 1))  
M1_data
```

```
> M1_data = M1%>%mutate(M1 = recode(M1, '20 - 40'= 0,'40 - 60'= 1))  
> M1_data  
      M1  
1 0  
2 0  
3 0  
4 0  
5 0  
6 0  
7 0  
8 0
```

# Moderating Variables

**Age (M1)**

**Gender (M2)**

**Annual income (M3)**

**Education level (M4)**

```
#M2 = Gender
```

```
M2 <- data.frame(data[,4])  
M2
```

```
M2_data = M2%>%mutate(M2 = recode(M2, 'Male'=1,'Female'=0))  
M2_data
```

```
#M3 = Income
```

```
M3 = data.frame(data[,5])  
M3
```

```
M3_data = M3%>%mutate(M3 = recode(M3, '0 - 2.5'=0,'2.5 - 5'=1,'5 - 10'=2,'10 and  
above'=3))  
M3_data
```

```
# ?recode()
```

```
#M4 - Education
```

```
M4 = data.frame(data[,6])  
M4
```

```
M4_data = M4%>%mutate(M4 = recode(M4, "Master's degree"=1,"Bachelor's degree"=0))  
M4_data
```

```
#### CALCULATING MEAN FOR EACH OF THE VARIABLES  
MVR_new$mean = rowMeans(MVR_new)  
MVMP$mean = rowMeans(MVMP)  
MVBA$mean = rowMeans(MVBA)  
MVFF$mean = rowMeans(MVFF)  
MVCK$mean = rowMeans(MVCK)  
MVSF$mean = rowMeans(MVSF)  
OVPB$mean = rowMeans(OVPB)
```

MVR\_new\$mean  
MVMP \$mean  
MVBA\$mean  
MVFF \$mean  
MVCK\$mean  
MVSF \$mean  
OVPB \$mean

```
# creating a data frame combining all average column,moderating column and outcome column
MODERATING_DATA =data.frame(MVR_new$mean ,MVMP$mean ,MVBA$mean ,MVFF$mean ,MVCK$mean ,MVSF$mean ,M1_data
,M2_data,M3_data,M4_data,OVPB$mean)
MODERATING_DATA

head(MODERATING_DATA)
```

```
> head(MODERATING_DATA)
   MVR_new.mean MVMP.mean MVBA.mean MVFF.mean MVCK.mean MVSF.mean M1 M2 M3 M4 OVPB.mean
1      2.25       1.4    1.666667     4.00       2.0    2.333333  0  1  3  1      2.00
2      2.25       2.8    2.333333     3.50       3.0    3.666667  0  0  3  1      3.00
3      2.00       1.6    2.666667     2.50       3.0    2.333333  0  0  3  0      1.75
4      4.25       4.2    4.000000     4.00       3.5    3.666667  0  1  3  1      4.00
5      3.75       3.4    3.666667     4.00       3.5    3.666667  0  1  3  1      4.00
6      3.25       4.8    3.333333     4.25       5.0    4.000000  0  0  0  0      4.75
```

```
##### LINEAR REGRESSION #####
split = sample.split(MODERATING_DATA, splitRatio = 0.7)
train = subset(MODERATING_DATA, split = 'TRUE')
test = subset(MODERATING_DATA, split = 'FALSE')

Model1 = lm(MODERATING_DATA, data = train)
summary(Model1)
```

```
call:
lm(formula = MODERATING_DATA, data = train)

Residuals:
    Min      1Q  Median      3Q     Max 
-1.34710 -0.03158 -0.02315  0.07076  1.30048 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)  1.18287   0.48505   2.439   0.0160 *  
MVMP.mean    0.59531   0.09615   6.191 6.71e-09 *** 
MVBA.mean    0.07090   0.07540   0.940   0.3487    
MVFF.mean   -0.13623   0.10399  -1.310   0.1924    
MVCK.mean   -0.13385   0.07506  -1.783   0.0768 .  
MVSF.mean    0.01337   0.08176   0.163   0.8704    
M1          -0.86243   0.15579  -5.536 1.56e-07 *** 
M2          0.42362   0.09743   4.348 2.69e-05 *** 
M3          0.08641   0.04435   1.948   0.0535 .  
M4          -0.01899   0.09622  -0.197   0.8439    
OVPB.mean    0.16016   0.07477   2.142   0.0340 *  
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.3443 on 135 degrees of freedom
Multiple R-squared:  0.6061,    Adjusted R-squared:  0.5769 
F-statistic: 20.77 on 10 and 135 DF,  p-value: < 2.2e-16
```

```
model1 <- lm(OVPB.mean ~ MVR_new.mean * M1 ,MODERATING_DATA)
summary(model1)
```

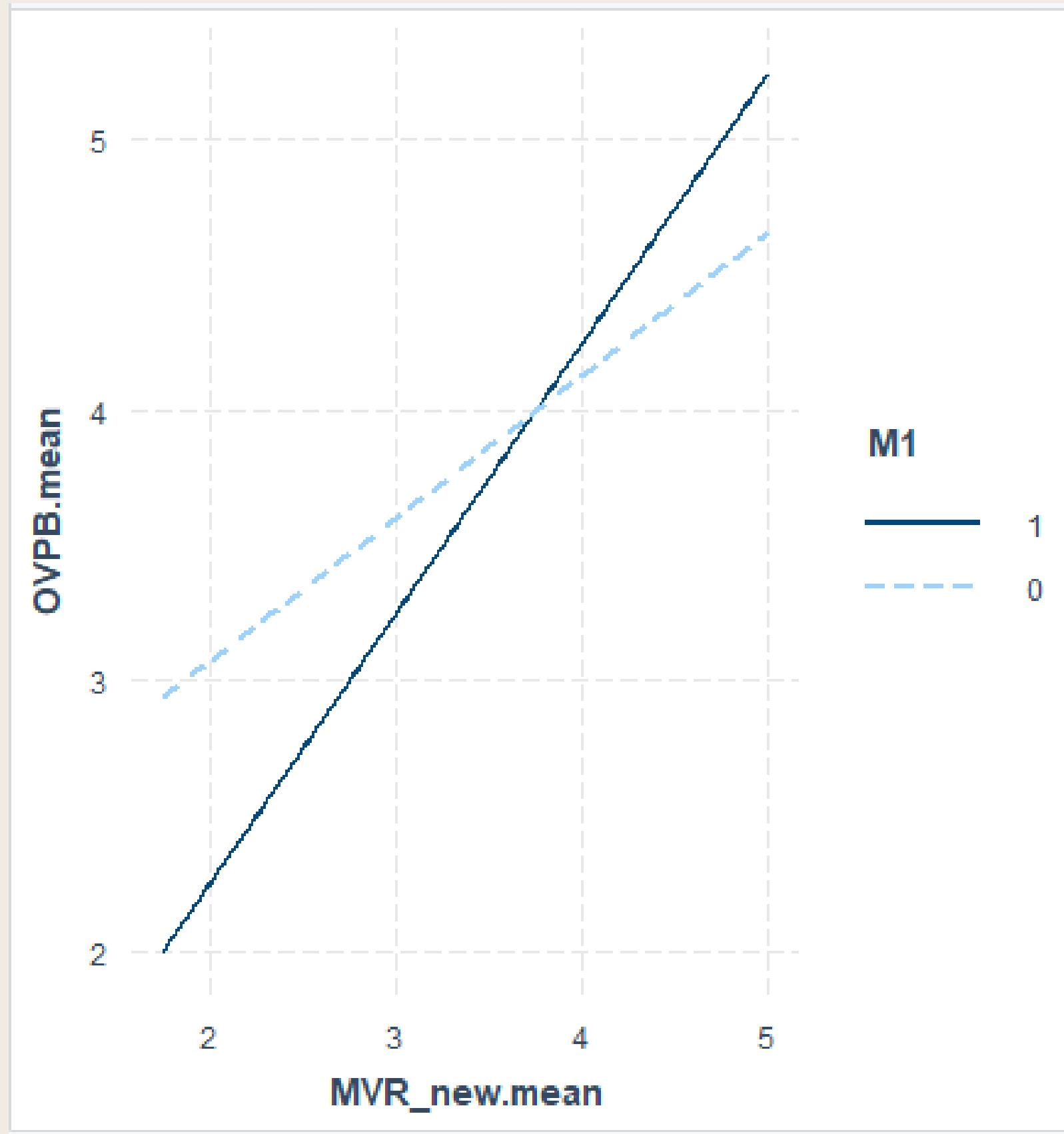
```
Call:
lm(formula = OVPB.mean ~ MVR_new.mean * M1, data = MODERATING_DATA)

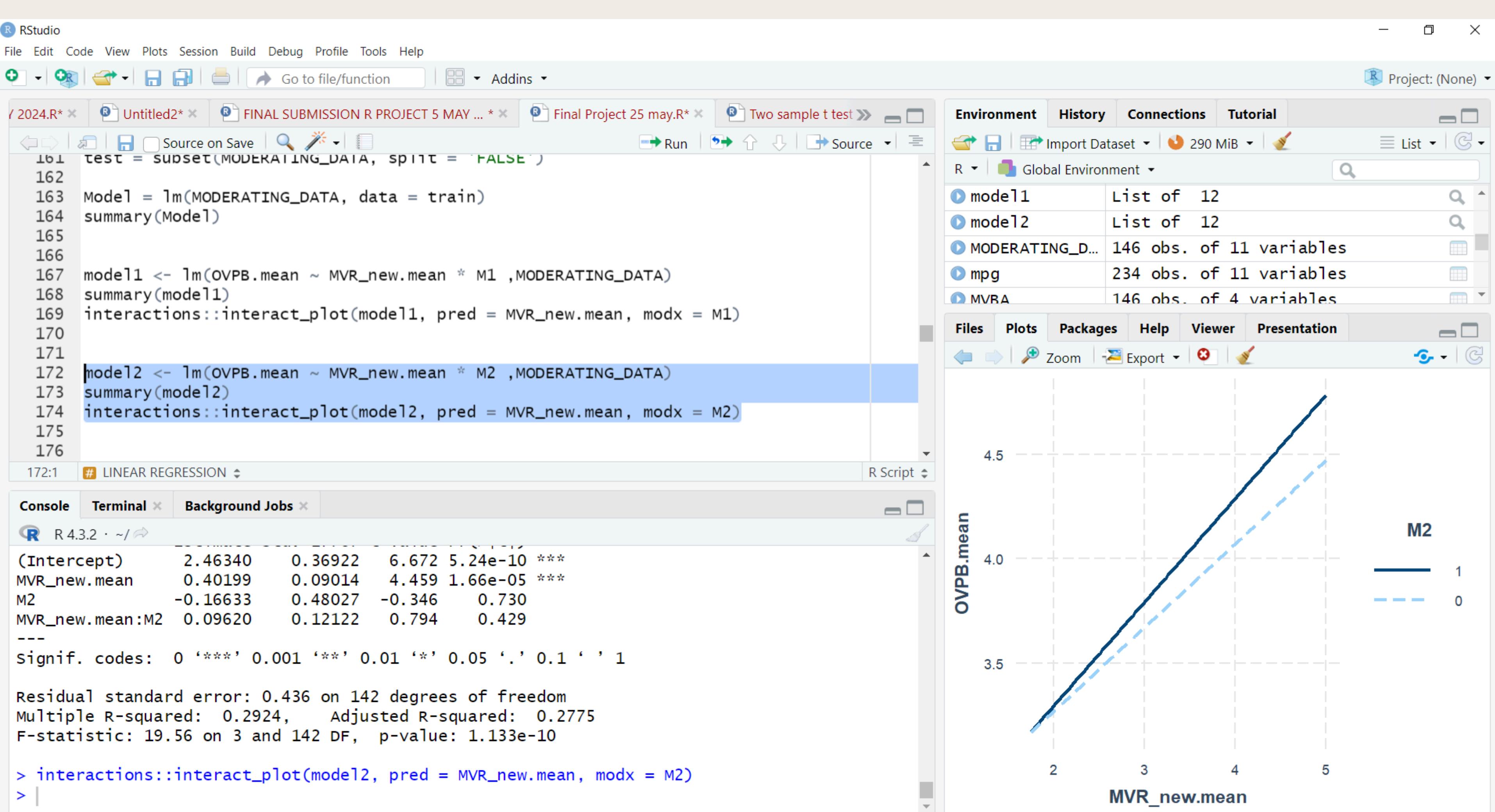
Residuals:
    Min      1Q  Median      3Q     Max 
-2.1303  0.0000  0.1049  0.1197  1.4140 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)  2.01217   0.29249   6.880 1.77e-10 ***
MVR_new.mean 0.52954   0.07082   7.478 7.16e-12 ***
M1          -1.76217   6.62274  -0.266   0.791    
MVR_new.mean:M1 0.47046   1.76240   0.267   0.790    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.4341 on 142 degrees of freedom
Multiple R-squared:  0.2985,    Adjusted R-squared:  0.2836 
F-statistic: 20.14 on 3 and 142 DF,  p-value: 6.226e-11
```

```
interactions::interact_plot(model1, pred = MVR_new.mean, modx = M1)
```





```

model24 <- lm(OVPB.mean ~ MVSF.mean * M4 ,MODERATING_DATA)
summary(model24)
interactions:::interact_plot(model24, pred = MVSF.mean, modx = M4)

```

```

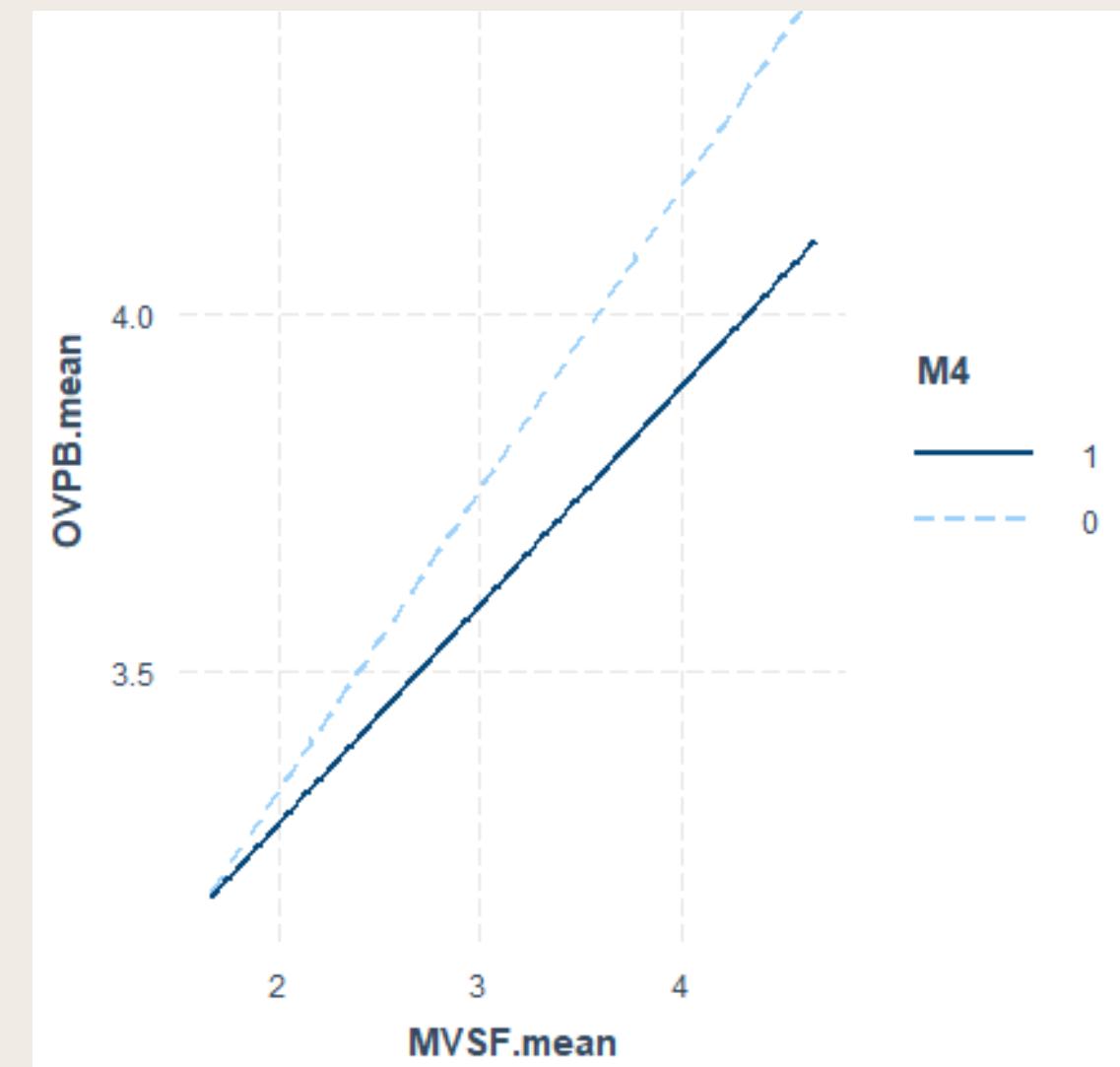
call:
lm(formula = OVPB.mean ~ MVSF.mean * M4, data = MODERATING_DATA)

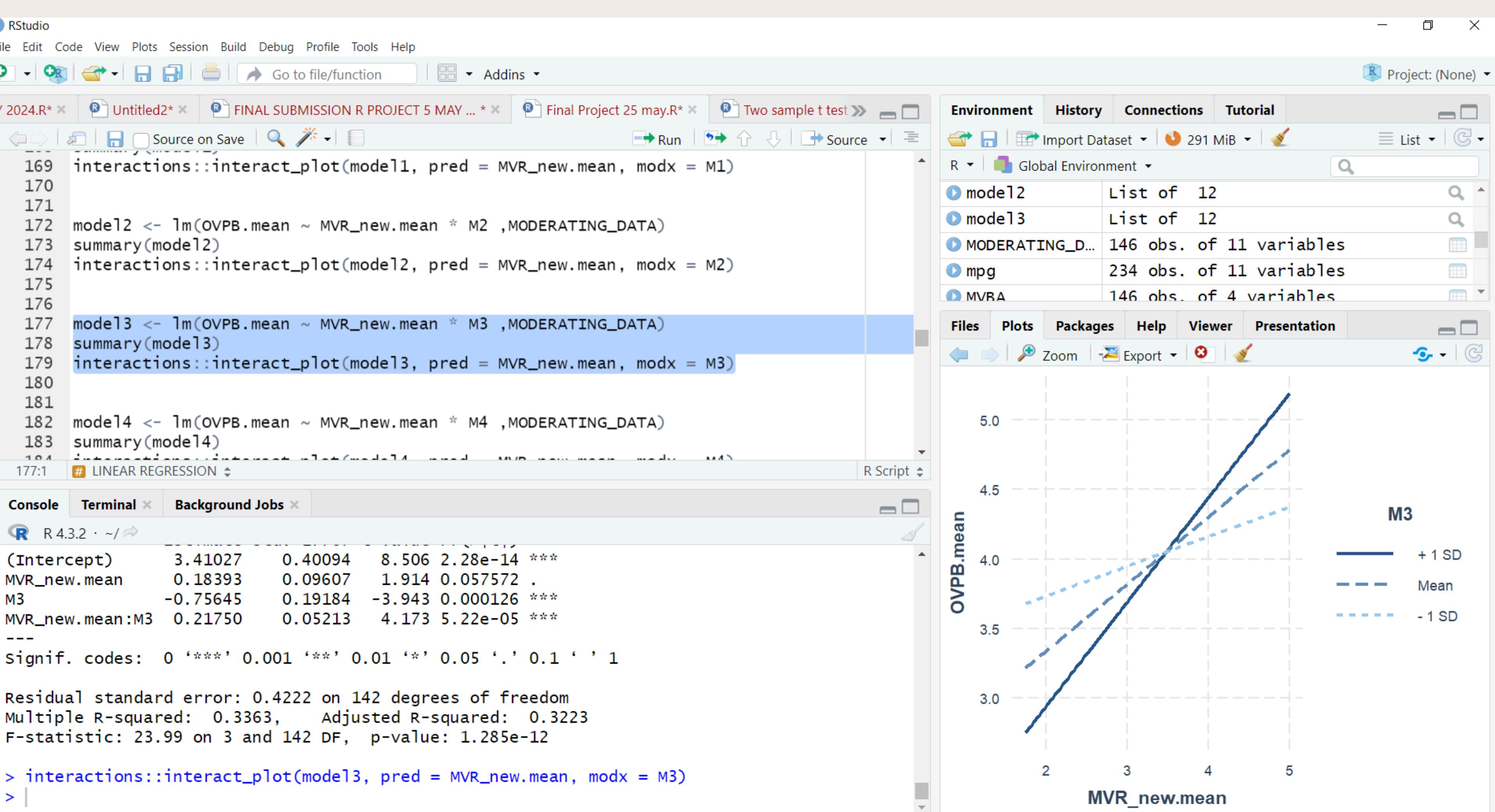
Residuals:
    Min      1Q  Median      3Q     Max 
-2.10364 -0.20759 -0.03647  0.18278  1.20172 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) 2.49237   0.33243   7.497 6.43e-12 ***
MSV.mean    0.42112   0.08061   5.224 6.11e-07 ***
M4          0.18626   0.57312   0.325   0.746    
MSV.mean:M4 -0.11576   0.14931  -0.775   0.439    
---
signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.4413 on 142 degrees of freedom
Multiple R-squared:  0.2749, Adjusted R-squared:  0.2596 
F-statistic: 17.95 on 3 and 142 DF,  p-value: 6.248e-10

```





```

/ 2024.R* x  Untitled2* x  FINAL SUBMISSION R PROJECT 5 MAY ... * x  Final Project 25 may.R* x  Two sample t test >
172 model12 <- lm(OVPB.mean ~ MVR_new.mean * M2 ,MODERATING_DATA)
173 summary(model12)
174 interactions::interact_plot(model12, pred = MVR_new.mean, modx = M2)
175
176
177 model13 <- lm(OVPB.mean ~ MVR_new.mean * M3 ,MODERATING_DATA)
178 summary(model13)
179 interactions::interact_plot(model13, pred = MVR_new.mean, modx = M3)
180
181
182 model14 <- lm(OVPB.mean ~ MVR_new.mean * M4 ,MODERATING_DATA)
183 summary(model14)
184 interactions::interact_plot(model14, pred = MVR_new.mean, modx = M4)
185 # ?interact_plot
186
187 model15 <- lm(OVPB.mean ~ MVMP.mean * M1 ,MODERATING_DATA)

```

182:1 # LINEAR REGRESSION

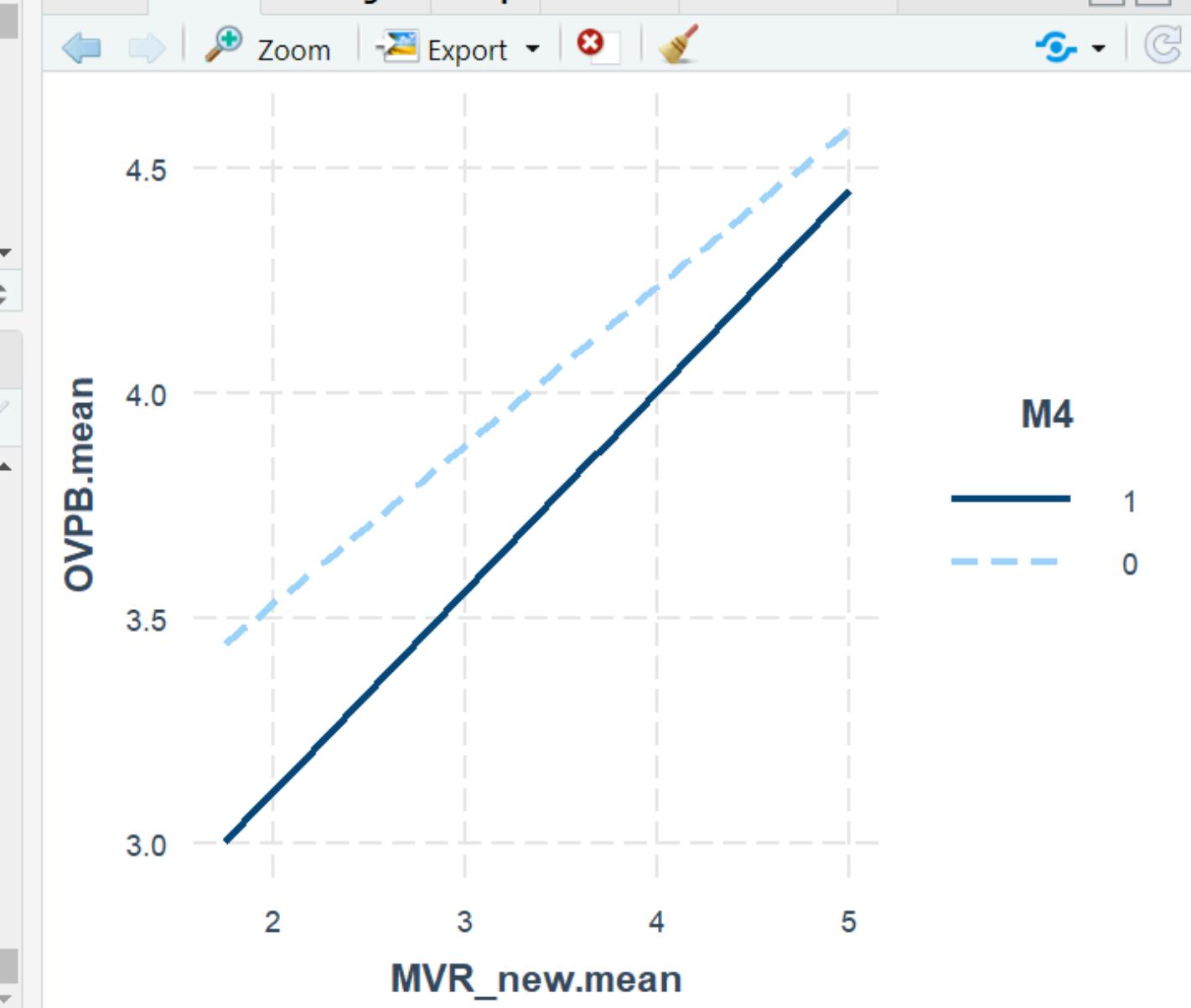
Environment History Connections Tutorial

Import Dataset 295 MiB

R Global Environment

- model13 List of 12
- model14 List of 12
- MODERATING\_D... 146 obs. of 11 variables
- mpg 234 obs. of 11 variables
- MVRA 146 obs. of 4 variables

Files Plots Packages Help Viewer Presentation



Console Terminal Background Jobs

R 4.3.2 · ~/

```

(Intercept) 2.82656 0.27009 10.465 < 2e-16 ***
MVR_new.mean 0.35261 0.06778 5.202 6.74e-07 ***
M4 -0.60291 0.55860 -1.079 0.282
MVR_new.mean:M4 0.09283 0.15255 0.609 0.544
---
signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.4358 on 142 degrees of freedom
Multiple R-squared: 0.293, Adjusted R-squared: 0.2781
F-statistic: 19.62 on 3 and 142 DF, p-value: 1.067e-10

> interactions::interact_plot(model14, pred = MVR_new.mean, modx = M4)
>

```

```

/ 2024.R* R Untitled2* R FINAL SUBMISSION R PROJECT 5 MAY ... * R Final Project 25 may.R* R Two sample t test >
summary(mode13)
179 interactions::interact_plot(model13, pred = MVR_new.mean, modx = M3)
180
181
182 model14 <- lm(OVPB.mean ~ MVR_new.mean * M4 ,MODERATING_DATA)
183 summary(model14)
184 interactions::interact_plot(model14, pred = MVR_new.mean, modx = M4)
185 # ?interact_plot
186
187 model15 <- lm(OVPB.mean ~ MVMP.mean * M1 ,MODERATING_DATA)
188 summary(model15)
189 interactions::interact_plot(model15, pred = MVMP.mean, modx = M1)
190
191
192 model16 <- lm(OVPB.mean ~ MVMP.mean * M2 ,MODERATING_DATA)
193 summary(model16)

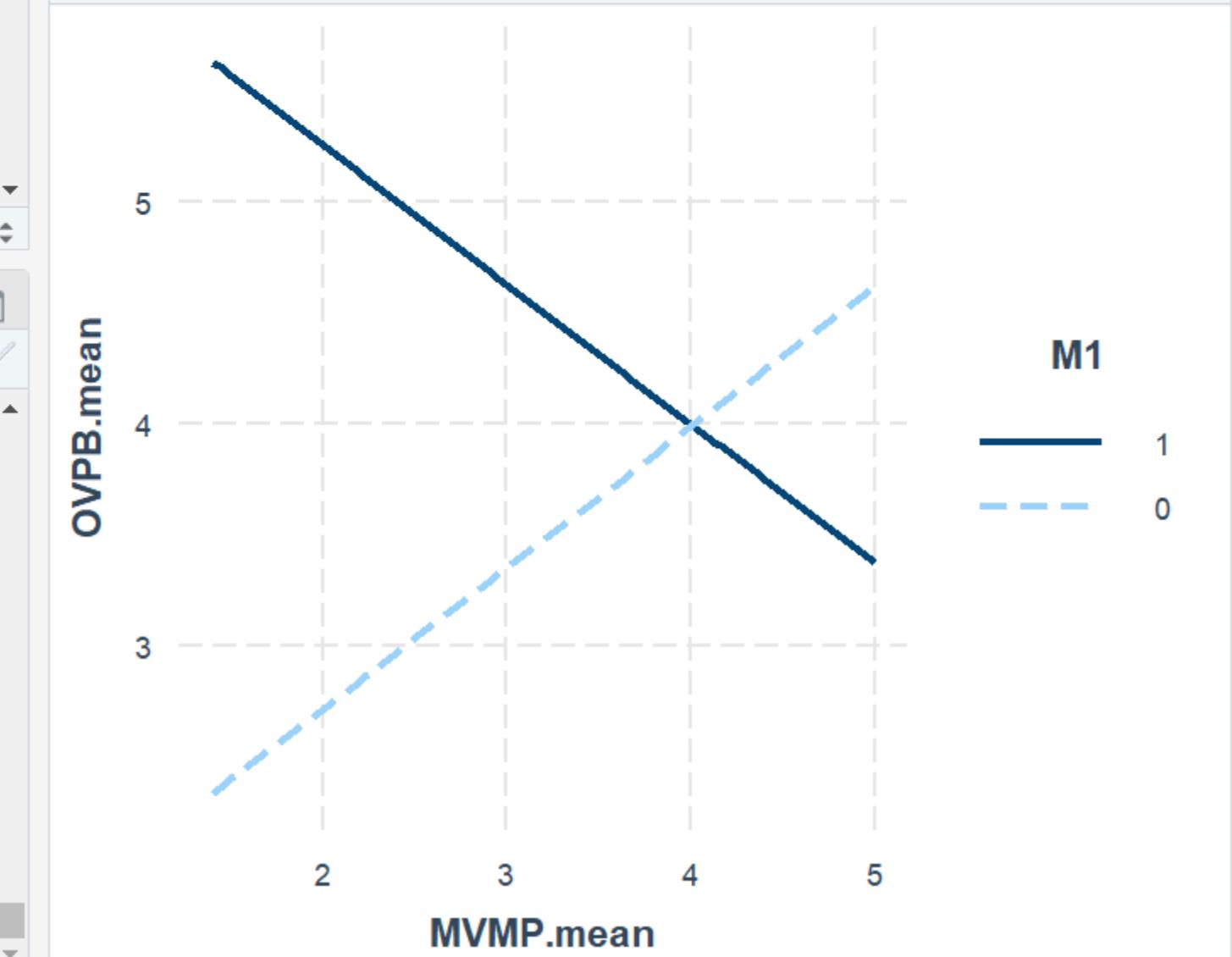
```

187:1 # LINEAR REGRESSION

Environment	
mode14	List of 12
mode15	List of 12
MODERATING_D...	146 obs. of 11 variables
mpg	234 obs. of 11 variables
MVRA	146 obs. of 4 variables

Files Plots Packages Help Viewer Presentation

Zoom Export



Console Terminal Background Jobs

R 4.3.2 · ~/

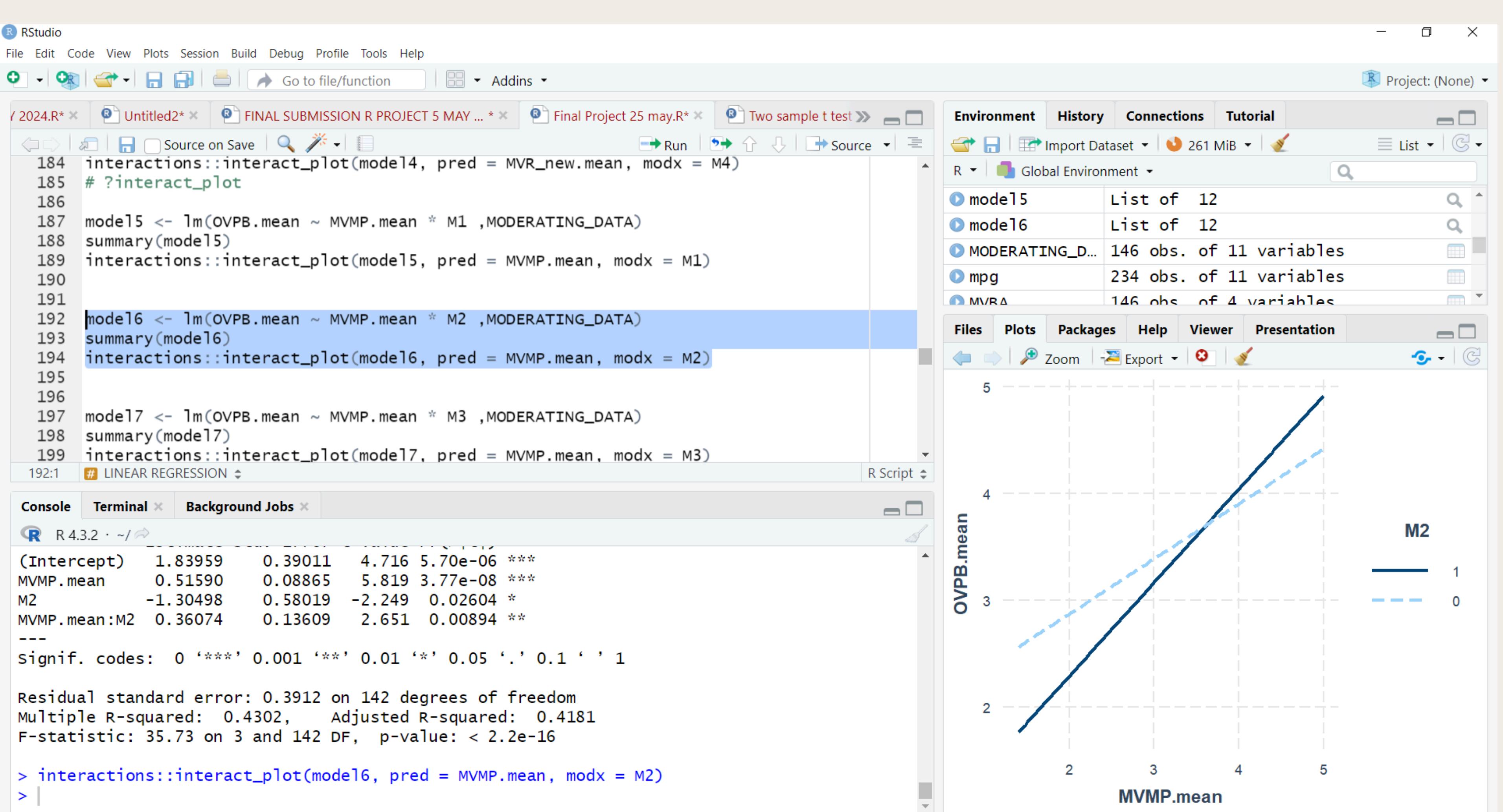
```

(Intercept) 1.45216 0.31286 4.642 7.79e-06 ***
MVMP.mean 0.63348 0.07215 8.780 4.73e-15 ***
M1 5.04784 4.18493 1.206 0.230
MVMP.mean:M1 -1.25848 1.04855 -1.200 0.232
---
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.4126 on 142 degrees of freedom
Multiple R-squared: 0.3663, Adjusted R-squared: 0.3529
F-statistic: 27.36 on 3 and 142 DF, p-value: 5.041e-14

> interactions::interact_plot(model15, pred = MVMP.mean, modx = M1)
>

```



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RStudio

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Addins

/ 2024.R\* Untitled2\* FINAL SUBMISSION R PROJECT 5 MAY ... \* Final Project 25 may.R Two sample t test

Source on Save Run Source

```

188 summary(model5)
189 interactions::interact_plot(model5, pred = MVMP.mean, modx = M1)
190
191
192 model6 <- lm(OVPB.mean ~ MVMP.mean * M2 ,MODERATING_DATA)
193 summary(model6)
194 interactions::interact_plot(model6, pred = MVMP.mean, modx = M2)
195
196
197 model7 <- lm(OVPB.mean ~ MVMP.mean * M3 ,MODERATING_DATA)
198 summary(model7)
199 interactions::interact_plot(model7, pred = MVMP.mean, modx = M3)
200
201
202 model8 <- lm(OVPB.mean ~ MVMP.mean * M4 ,MODERATING_DATA)
203 summary(model8)

```

# LINEAR REGRESSION

Console Terminal Background Jobs

R 4.3.2

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	2.53982	0.59686	4.255	3.77e-05 ***
MVMP.mean	0.38088	0.13477	2.826	0.00539 **
M3	-0.55796	0.24308	-2.295	0.02318 *
MVMP.mean:M3	0.13667	0.05717	2.391	0.01812 *

---

Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.4062 on 142 degrees of freedom  
 Multiple R-squared: 0.3856, Adjusted R-squared: 0.3727  
 F-statistic: 29.71 on 3 and 142 DF, p-value: 5.71e-15

> interactions::interact\_plot(model7, pred = MVMP.mean, modx = M3)

Environment History Connections Tutorial

Import Dataset 164 MiB

Global Environment

- model13 List of 12
- model14 List of 12
- model15 List of 12
- model16 List of 12
- model17 List of 12

Files Plots Packages Help Viewer Presentation

Zoom Export

OVPB.mean

MVMP.mean

+ 1 SD

Mean

- 1 SD

M3

**Similarly we create 24 models and visualized it using interactions**

Type here to search

RStudio

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Go to file/function Addins

Project: (None)

```
192 model16 <- lm(OVPB.mean ~ MVMP.mean * M2 ,MODERATING_DATA)
193 summary(model16)
194 interactions::interact_plot(model16, pred = MVMP.mean, modx = M2)
195
196
197 model17 <- lm(OVPB.mean ~ MVMP.mean * M3 ,MODERATING_DATA)
198 summary(model17)
199 interactions::interact_plot(model17, pred = MVMP.mean, modx = M3)
200
201
202 model18 <- lm(OVPB.mean ~ MVMP.mean * M4 ,MODERATING_DATA)
203 summary(model18)
204 interactions::interact_plot(model18, pred = MVMP.mean, modx = M4)
205
206
207 model19 <- lm(OVPB.mean ~ MVBA.mean * M1 ,MODERATING_DATA)
208 summary(model19)
209 # LINEAR REGRESSION
```

Console Terminal Background Jobs

R 4.3.2 · ~/

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	0.99406	0.40522	2.453	0.01537 *
MVMP.mean	0.75198	0.09419	7.983	4.37e-13 ***
M4	1.31022	0.56949	2.301	0.02287 *
MVMP.mean:M4	-0.37671	0.13665	-2.757	0.00661 **

---

Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.3937 on 142 degrees of freedom  
Multiple R-squared: 0.4228, Adjusted R-squared: 0.4106  
F-statistic: 34.68 on 3 and 142 DF, p-value: < 2.2e-16

Environment History Connections Tutorial

Import Dataset 164 MiB

Global Environment

model14 List of 12
model15 List of 12
model16 List of 12
model17 List of 12
model18 List of 12

Files Plots Packages Help Viewer Presentation

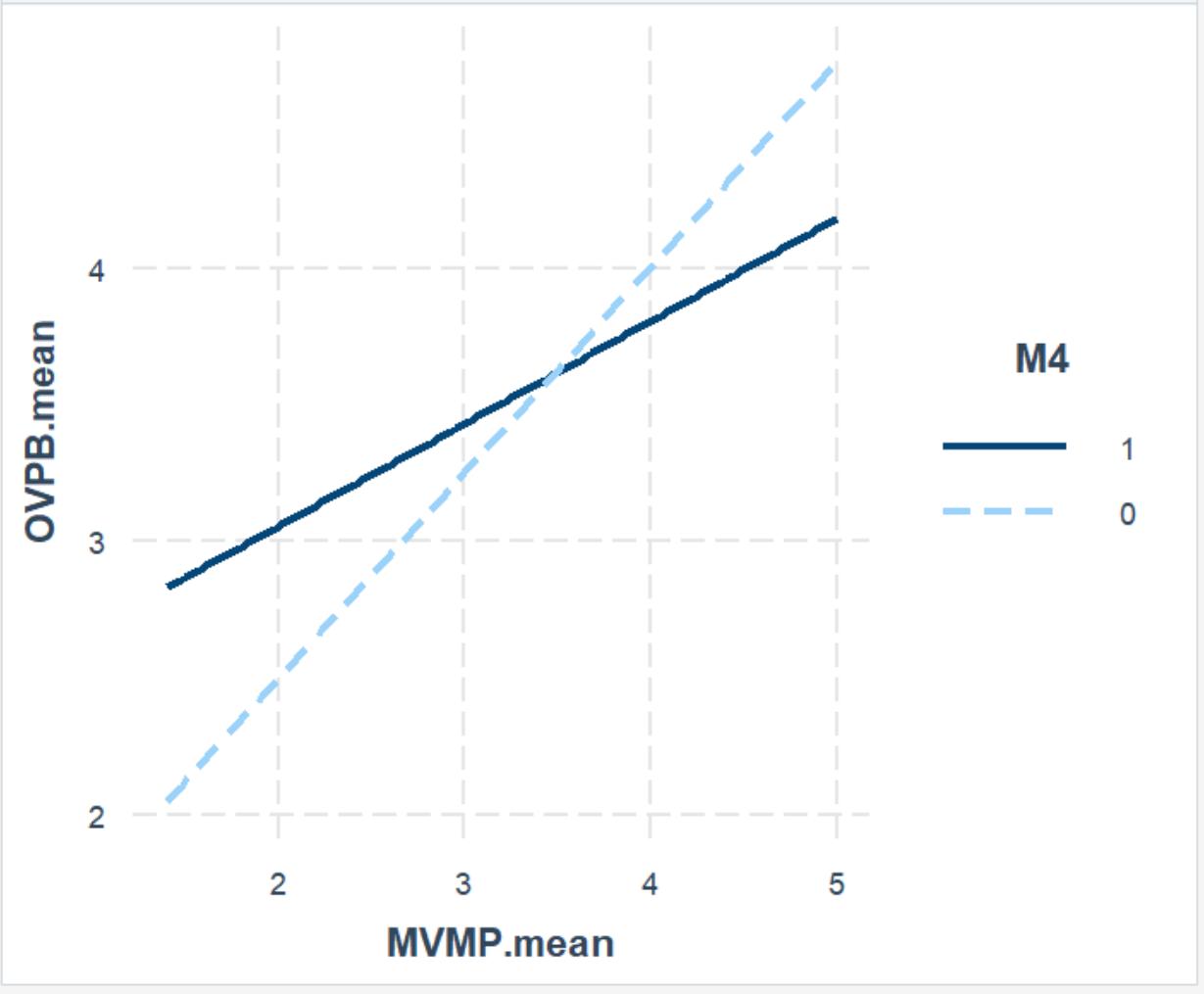
OVPB.mean

M4

2 3 4 5

2 3 4 5

Run Source



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Addins

/ 2024.R\* Untitled2\* FINAL SUBMISSION R PROJECT 5 MAY ... \* Final Project 25 may.R Two sample t test

Source on Save Run Source

```

196
197 model17 <- lm(OVPB.mean ~ MVMP.mean * M3 ,MODERATING_DATA)
198 summary(model17)
199 interactions::interact_plot(model17, pred = MVMP.mean, modx = M3)
200
201
202 model18 <- lm(OVPB.mean ~ MVMP.mean * M4 ,MODERATING_DATA)
203 summary(model18)
204 interactions::interact_plot(model18, pred = MVMP.mean, modx = M4)
205
206
207 model19 <- lm(OVPB.mean ~ MVBA.mean * M1 ,MODERATING_DATA)
208 summary(model19)
209 interactions::interact_plot(model19, pred = MVBA.mean, modx = M1)
210
211 # LINEAR REGRESSION

```

Environment History Connections Tutorial

Import Dataset 165 MiB

Global Environment

mode15 List of 12  
mode16 List of 12  
mode17 List of 12  
mode18 List of 12  
mode19 List of 12

Files Plots Packages Help Viewer Presentation

OVPB.mean

MVBA.mean

M1

4.50

4.25

4.00

3.75

2 3 4 5

Console Terminal Background Jobs

R 4.3.2 · ~/

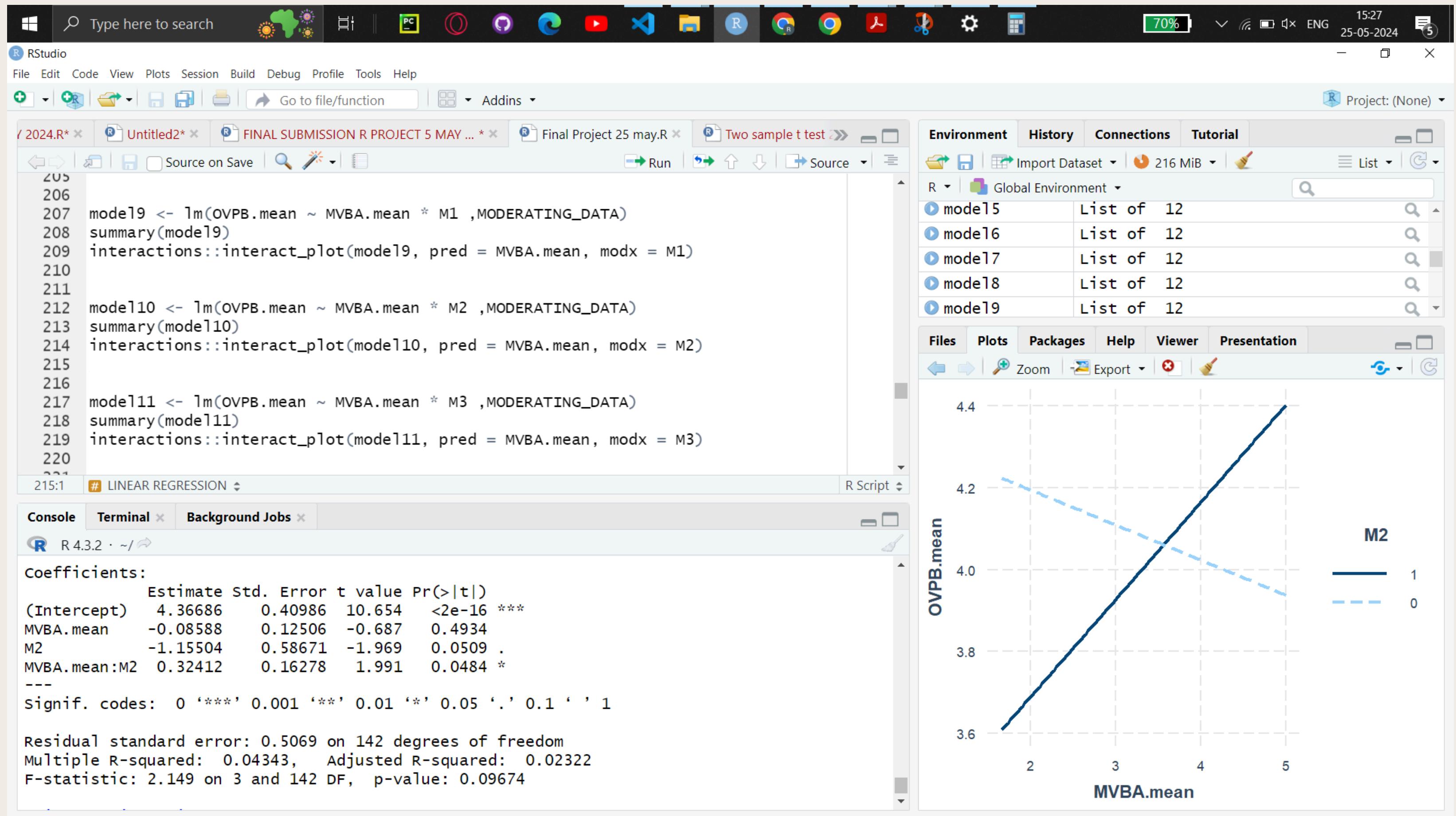
Coefficients:

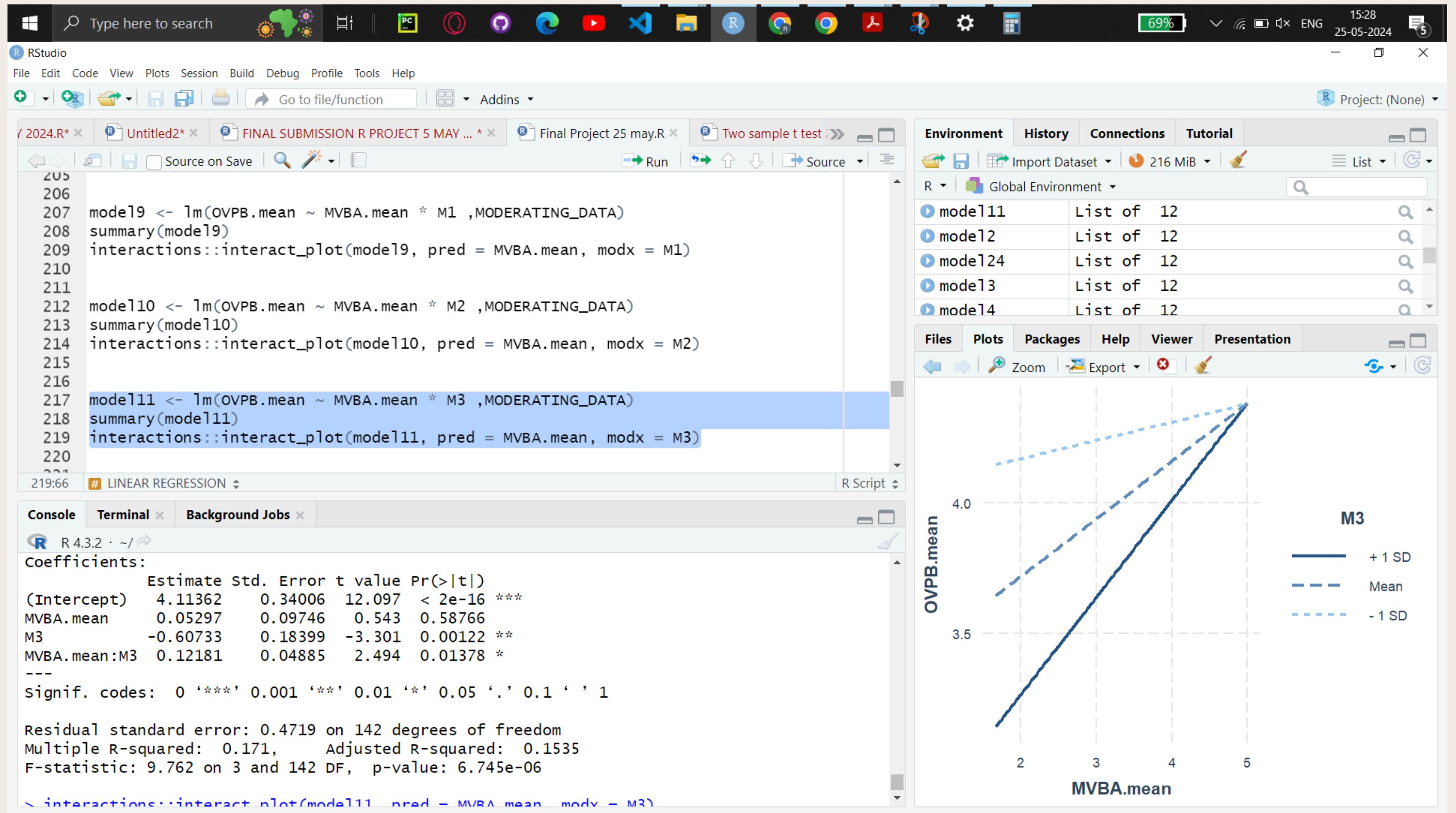
	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	3.33029	0.27231	12.230	< 2e-16 ***
MVBA.mean	0.24158	0.07649	3.158	0.00194 **
M1	1.75304	2.18173	0.804	0.42302
MVBA.mean:M1	-0.49158	0.50819	-0.967	0.33503

Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.4954 on 142 degrees of freedom  
Multiple R-squared: 0.0864, Adjusted R-squared: 0.0671  
F-statistic: 4.476 on 3 and 142 DF, p-value: 0.004913

> interactions::interact\_plot(model19, pred = MVBA.mean, modx = M1)





Type here to search

RStudio

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Addins

Project: (None)

```
/ 2024.R* R Untitled2* R FINAL SUBMISSION R PROJECT 5 MAY ... * R Final Project 25 may.R R Two sample t test
```

Source on Save Run Source

214 interactions::interact\_plot(model10, pred = MVBA.mean, modx = M2)  
215  
216 model11 <- lm(OVPB.mean ~ MVBA.mean \* M3 ,MODERATING\_DATA)  
217 summary(model11)  
218 interactions::interact\_plot(model11, pred = MVBA.mean, modx = M3)  
219  
220 model12 <- lm(OVPB.mean ~ MVBA.mean \* M4 ,MODERATING\_DATA)  
221 summary(model12)  
222 interactions::interact\_plot(model12, pred = MVBA.mean, modx = M4)  
223  
224 model13 <- lm(OVPB.mean ~ MVFF.mean \* M1 ,MODERATING\_DATA)  
225 summary(model13)  
226 interactions::interact\_plot(model13, pred = MVFF.mean, modx = M1)

# LINEAR REGRESSION

Console Terminal Background Jobs

R 4.3.2 ~/

```
(Intercept) 4.08438 0.29290 13.945 <2e-16 ***  
MVBA.mean 0.03493 0.07674 0.455 0.650  
M4 -0.57352 0.51033 -1.124 0.263  
MVBA.mean:M4 0.04813 0.14184 0.339 0.735  
---  
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Residual standard error: 0.489 on 142 degrees of freedom  
Multiple R-squared: 0.1097, Adjusted R-squared: 0.09092  
F-statistic: 5.834 on 3 and 142 DF, p-value: 0.0008695

```
> interactions::interact_plot(model12, pred = MVBA.mean, modx = M4)  
>
```

Environment History Connections Tutorial

Import Dataset 216 MiB

Global Environment

model12 List of 12  
model12 List of 12  
model24 List of 12  
model13 List of 12  
model14 List of 12

Files Plots Packages Help Viewer Presentation

Zoom Export

OVPB.mean

M4

1

0

MVBA.mean



```

272 model122 <- lm(OVPB.mean ~ MVSF.mean * M2 ,MODERATING_DATA)
273 summary(model122)
274 interactions::interact_plot(model122, pred = MVSF.mean, modx = M2)
275
276
277 model123 <- lm(OVPB.mean ~ MVSF.mean * M3 ,MODERATING_DATA)
278 summary(model123)
279 interactions::interact_plot(model123, pred = MVSF.mean, modx = M3)
280
281
282 model124 <- lm(OVPB.mean ~ MVSF.mean * M4 ,MODERATING_DATA)
283 summary(model124)
284 interactions::interact_plot(model124, pred = MVSF.mean, modx = M4)
285
286

```

282:1 # LINEAR REGRESSION

Environment History Connections Tutorial

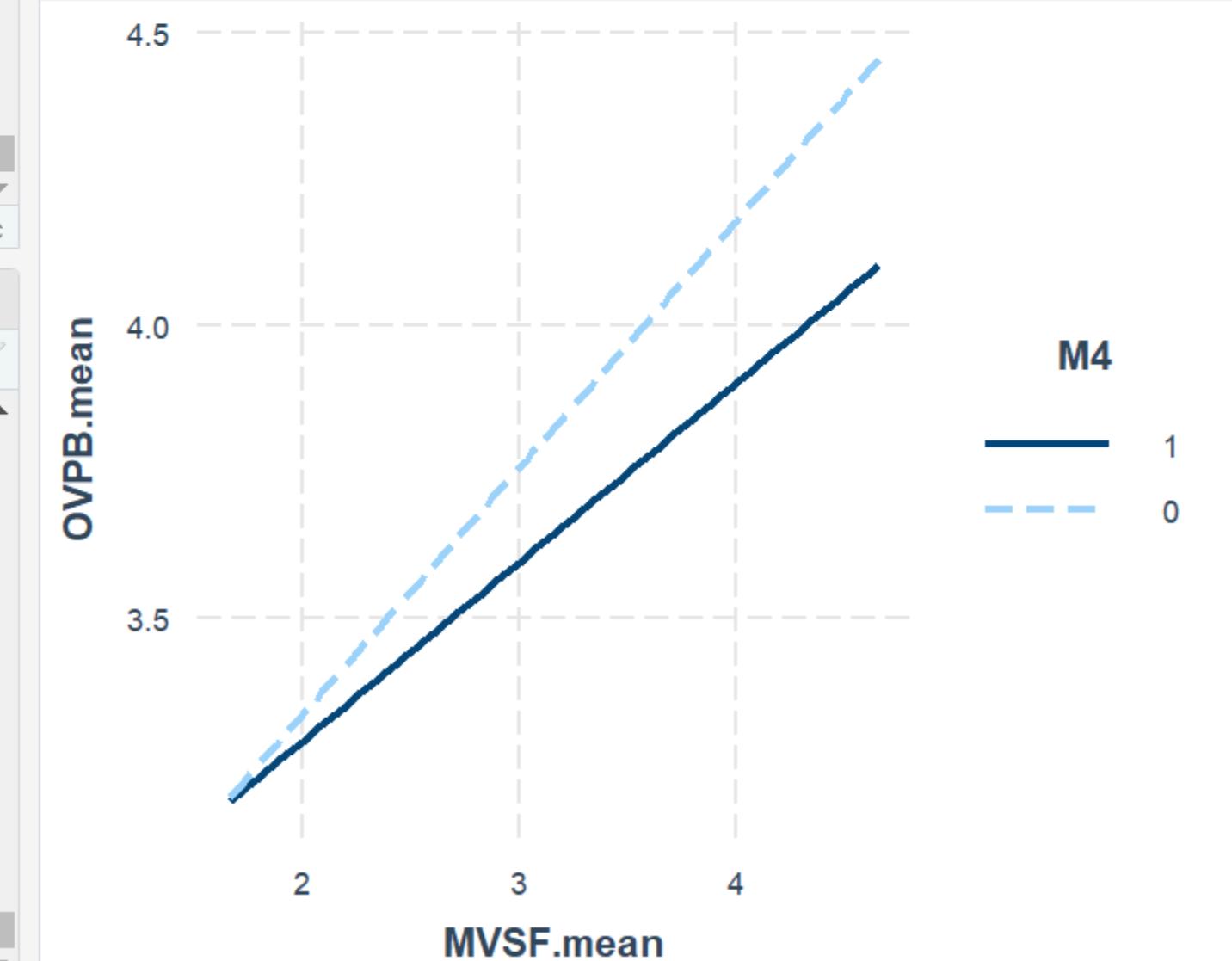
Import Dataset 262 MiB

R Global Environment

- model124 List of 12
- model13 List of 12
- model14 List of 12
- model15 List of 12
- model16 List of 12

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R 4.3.2 · ~/

```

(Intercept) 2.49237 0.33243 7.497 6.43e-12 ***
MVSF.mean 0.42112 0.08061 5.224 6.11e-07 ***
M4 0.18626 0.57312 0.325 0.746
MVSF.mean:M4 -0.11576 0.14931 -0.775 0.439
---
signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.4413 on 142 degrees of freedom
Multiple R-squared: 0.2749, Adjusted R-squared: 0.2596
F-statistic: 17.95 on 3 and 142 DF, p-value: 6.248e-10

> interactions::interact_plot(model124, pred = MVSF.mean, modx = M4)
>

```

**THANK  
YOU VERY  
MUCH!**

