Investigating the Effect of a Recommendation Badge on Food Choices

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Introduction

Our project is centered on consumer analytics and the presentation of food alternatives on applications. Understanding how customers make their decisions is critical in today's environment, especially with the development of meal delivery apps and the convenience they provide. According to Business Insider, the meal delivery sector will be worth $161.7 billion by 2023. As a result, we wanted to investigate how specific app features, such as a suggestion badge, influence the consumer's decision-making process. Additionally, we intend to explore how this differs by gender, budget choices, and age.

Methodology

Experiment goal

This experiment aims to observe how a recommendation badge on the left option picture affects the consumer's choice. Our control group consists of questions that do not have a recommendation badge, where we will analyze if people choose the right or left picture. Additionally, we want to examine how the experiment results vary according to demographic factors such as gender, budget preferences, and age. By doing so, we hope to gain insights into consumer behavior and how app developers can optimize the presentation of food options to increase consumer engagement and satisfaction.

Hypothesis

Based on our goal, our hypothesis is that having a badge on the picture on the left affects the decision of the people while choosing meal options.

Survey Design

The survey was designed using the Qualtrics platform, which included control and treatment groups with randomized questions for all participants. The survey began with one question about the participant's diet, age, gender identity, and spending habits while ordering a meal. Each participant had three treatment questions and three control questions.

Non-vegetarian and Vegetarian questions assignment

The survey had two distinct categories based on participants' dietary preferences: Vegetarian and Non-vegetarian. Vegetarian participants would be disqualified from proceeding further, while Non-vegetarian participants were presented with six questions. Each question offered two dish options, and participants were required to select one.

Control and treatment assignment

All participants were assigned to both control and treatment groups, with three out of six questions having a treatment where the left option was marked with a recommended badge and the remaining three being control questions where both dish options had no recommended tag. Participants were required to choose one option out of the two provided. Two main components in the survey were treatment (whether the option selected was a treatment question or not) and clicked_left_option (whether the participant chose the left or right option).

Survey questions design

The survey starts with a basic introduction to our experiment, a general information question, and the main body of the survey. In the survey introduction we briefly explained what they survey is about, the next question is about diet preferences based on which they move ahead in the survey. The survey includes a block for vegetarian participants, focusing mainly on non-vegetarian participants who were presented with six question, each had two options and the respondents were asked to choose one. The treatment group had a recommended badge on the left option, while the control group had no badge. Each participant was part of both the control and treatment groups which was recorded as treatment (if it's a treatment question or not), and their selection was recorded under clicked_left_option (if they chose left option or not). The survey's main goal was to analyze the impact of the recommended badge on the left option on participants' choices and determine if it influenced their selection.

Randomization at question level

We randomized at question level, which means participants were not divided into treatment and control groups, and each participant received 3 choices from the treatment questions and 3 choices from the control questions. The Qualtrics allows us to randomize the questions in order. So, each respondent would have a random order for questions.

Scoring

Each respondent's score is calculated based on the type of question (either control or treatment) and their choice (either left or right). Our data has a column called "Treatment" indicating whether the question being answered is a control or treatment question, not having or having the recommended badge. The column "Clicked_Left_Option" shows the image that the person chose. It assigns a value of 1 if they picked the left and 0 if they picked the right.

Procedure

Before rolling out the survey, we conducted a small pilot study by sending out the survey to 5 people. We checked if the questions were straightforward and if the participants did not choose the exact products due to bias, like the food item's appeal in the picture. As expected, the responses were mixed, and we finally rolled out the survey mainly to Boston University students and some friends in the age range of 20-30 years, and family members. We primarily targeted the non-vegetarian population as our survey is centered on non-vegetarian food and hoped to collect at least 60 responses. We received a quick response from all students and friends, and 81 people finished the survey, out of which 11 were vegetarians and 70 non-vegetarian participants.

Data Analysis

Data Cleaning

To ensure the quality of our data analysis, we examined the survey responses and identified incomplete surveys and duplicates. We removed unfinished surveys and those submitted by vegetarian users who were automatically disqualified. Using Python, we cleaned the data and eliminated unnecessary columns such as "DistributionChannel" and "UserLanguage".

```
data <- fread('final_data.csv')
data$Gender[data$Gender == "Male"] <- 0 # male
data$Gender[data$Gender == "Female"] <- 1 # female
```

Exploratory Data Analysis

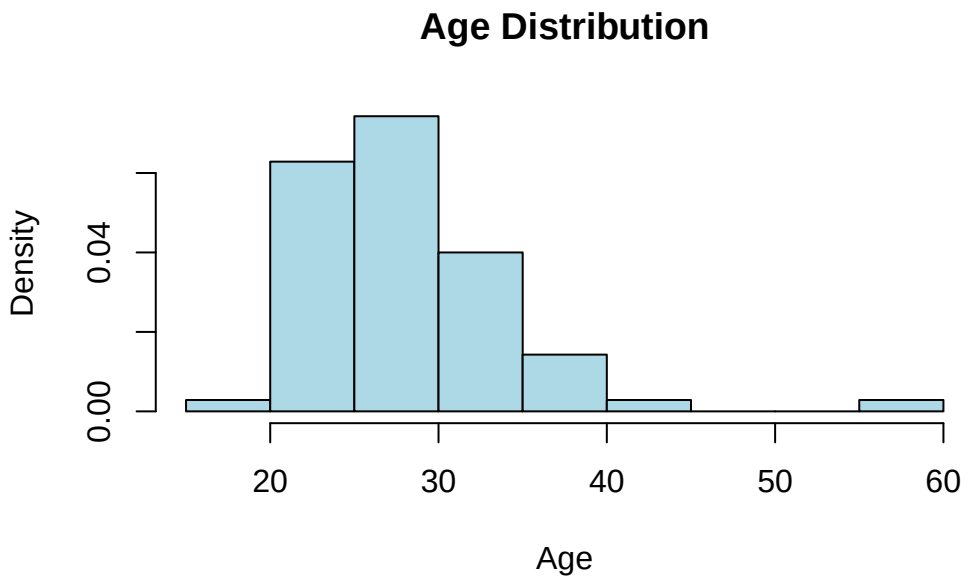
We did some Exploratory Data Analysis (EDA) to get an overview of our data.

```
# Number of control and treatment samples based on gender
data[,list(num_response = .N), by=list(Treatment, Gender)][order(Treatment, Gender)]
```

```
   Treatment Gender num_response
1:         0      0           96
2:         0      1          114
3:         1      0           96
4:         1      1          114
```

There were 96 responses from males who did not receive the treatment, 114 from females who did not, 96 from males who received the treatment, and 114 from females who received the treatment.

```
# Distribution of Age
hist(data$Age,main="Age Distribution",
xlab="Age",col="lightblue",freq=FALSE)
```

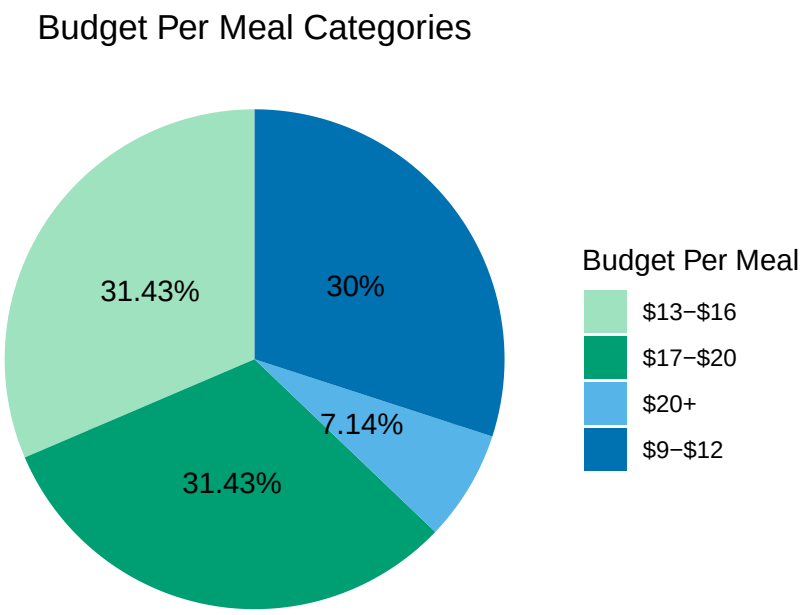


Most of the responses come from people in the age range of 20 to 35.

```
# Calculate the frequency count and percentage of each category
freq_table <- table(data$Budget_Per_Meal)
percent_table <- round(prop.table(freq_table) * 100,2)

df <- data.frame(Budget_Per_Meal = names(percent_table),
                 Percent = as.vector(percent_table))
my_palette <- c("#9FE2BF","#009E73", "#56B4E9", "#0072B2")

ggplot(df, aes(x="", y=Percent, fill=Budget_Per_Meal)) +
  geom_bar(stat="identity", width=1) + coord_polar("y", start=0) +
  theme_void() + labs(fill="Budget Per Meal") +
  geom_text(aes(label = paste0(Percent, "%")), position = position_stack(vjust = 0.5))+
  scale_fill_manual(values=my_palette) + ggtitle("Budget Per Meal Categories")+
  theme(plot.title = element_text(hjust = 0.5))
```



The pie chart reveals that 30% - 31% of the respondents prefer to spend between \$9-\$12, \$13-\$16, and \$17-\$20 for each meal, respectively. Additionally, about 7% of the respondents prefer to spend more than \$20 on a meal when ordering food.

Estimated Average Treatment Effect

```
ate_hat <- data[Treatment==1, mean(Clicked_Left_Option)] -
  data[Treatment==0, mean(Clicked_Left_Option)]
```

Regressions

```
simple_reg <- feols(Clicked_Left_Option ~ Treatment, data=data, se='white')
fe_reg <- feols(Clicked_Left_Option ~ Treatment | ResponseId , data=data, se='white')

modelsummary(list("Clicked Left Option" = simple_reg,
                  "Clicked Left Option (Fixed Effect)" = fe_reg
                  ), type = 'text', stars = T,
             output = 'markdown', gof_map = c("nobs", "r.squared"))
```

	Clicked Left Option	Clicked Left Option (Fixed Effect)
(Intercept)	0.543***	
	(0.034)	
Treatment	0.033	0.033
	(0.049)	(0.048)
Num.Obs.	420	420

	Clicked Left Option	Clicked Left Option (Fixed Effect)
R2	0.001	0.185

Note: ^^ + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

According to the above regression, we conclude the followings:

1. Since we randomized this experiment on the question level instead of the individual level, we collected a total number of observations of 420.
2. We ran a simple regression with the "Clicked_Left_Option" as the dependent variable and having a badge on the left option as the treatment. We also ran a fixed-effects linear regression model to control the individual-specific attributes with "ResponseId".
3. The estimated average treatment effect is 0.0333, and the standard error of this value is 0.049 using simple linear regression. This estimated ATE value is not statistically significant. And the result from the fixed-effects linear regression model is similar.
4. The p-values for both regressions are bigger than 0.05, meaning we cannot reject the hypothesis that the treatment does not affect the experiment outcome.
5. However, the R-squared for the fixed-effects linear regression model is much higher (0.185), indicating that controlling for the fixed effect of ResponseId explains more significant proportion of the variation in "Clicked_Left_Option".

Conditional Treatment Effect

The treatment effect might vary depending on subjects' budget level, and we conducted CATE calculations on different budget groups.

There are 4 budget groups in total, and we divided them into different segments.

```
Budget_1 <- data[Budget_Per_Meal == "$9-$12"]
Budget_2 <- data[Budget_Per_Meal == "$13-$16"]
Budget_3 <- data[Budget_Per_Meal == "$17-$20"]
Budget_4 <- data[Budget_Per_Meal == "$20+"]
```

```
reg_1 <- feols(Clicked_Left_Option ~ Treatment, data=Budget_1, se='white')
reg_2 <- feols(Clicked_Left_Option ~ Treatment, data=Budget_2, se='white')
reg_3 <- feols(Clicked_Left_Option ~ Treatment, data=Budget_3, se='white')
reg_4 <- feols(Clicked_Left_Option ~ Treatment, data=Budget_4, se='white')
modelsummary(list("Budget($9-12)" = reg_1, "Budget($13-16)" = reg_2,
                  "Budget($17-20)" = reg_3, "Budget($20+)" = reg_4), type = 'text',
             stars = T, output = 'markdown', gof_map = c("nobs", "r.squared"))
```

	Budget($9-12)	Budget($13-16)	Budget($17-20)	Budget($20+)
(Intercept)	0.556***	0.545***	0.545***	0.467**
	(0.063)	(0.062)	(0.062)	(0.133)
Treatment	0.000	0.061	0.015	0.133

	Budget($9-12)	Budget($13-16)	Budget($17-20)	Budget($20+)
	(0.089)	(0.087)	(0.087)	(0.187)
Num.Obs.	126	132	132	30
R2	0.000	0.004	0.000	0.018

Note: ^^ + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

The estimated conditional treatment effect for budget group 1 ("$9-$12") is 0. The estimated conditional treatment effect for budget group 2 ("$13-$16") is 0.06. The estimated conditional treatment effect for budget group 3 ("$17-$20") is 0.015. The estimated conditional treatment effect for budget group 4 ("$20+") is 0.133. None of above estimated conditional treatment effects are statistically significant.

Controlling a Covariate

```
#  Age,Gender,Budget_Per_Meal as a covariate
cov_gender <- feols(Clicked_Left_Option ~ Treatment + Gender, data=data, se='white')
cov_budget <- feols(Clicked_Left_Option ~ Treatment + Budget_Per_Meal,
                    data=data, se='white')

modelsummary(list("Reg(Gender as Cov)" = cov_gender,
                  "Reg(Budget as Cov)" = cov_budget,
                  "Simple Reg" = simple_reg, "Fixed Effect Reg" = fe_reg),
             type = 'text', stars = T, output = 'markdown',
             coef_map = c("(Intercept)" = "(Intercept)","Treatment"="Treatment",
                          "Gender1" = "Female",
                          "Budget_Per_Meal$9-$12" = "Budget Per Meal($9-$12)",
                          "Budget_Per_Meal$17-$20" = "Budget Per Meal($17-$20)",
                          "Budget_Per_Meal$20+" = "Budget Per Meal($20+)"),
             gof_map = c("nobs", "r.squared"))
```

	Reg(Gender as Cov)	Reg(Budget as Cov)	Simple Reg	Fixed Effect Reg
(Intercept)	0.551***	0.559***	0.543***	
	(0.043)	(0.050)	(0.034)	
Treatment	0.033	0.033	0.033	0.033
	(0.049)	(0.049)	(0.049)	(0.048)
Female	-0.015			
	(0.049)			
Budget Per Meal($9-$12)		-0.020		
		(0.062)		
Budget Per Meal($17-$20)		-0.023		
		(0.061)		

	Reg(Gender as Cov)	Reg(Budget as Cov)	Simple Reg	Fixed Effect Reg
Budget Per Meal($20+)		-0.042		
		(0.101)		
Num.Obs.	420	420	420	420
R2	0.001	0.002	0.001	0.185

Note: ^ + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

We incorporated gender and budget preferences as covariates to check whether the estimate's precision increases. As a result, the estimate of the average treatment effect and R-squared stayed mostly the same.

Randomization Check

Using the "Randomization" feature of Qualtrics, we applied complete randomization to ensure that all control or treatment group questions are in random order and each participant was a part of treatment and control group 3 times each. Hence, from 70 participants we collected 420 observations, and we had 210 in the control and treatment groups, respectively.

Statistical Power

```
cohens_d <- ate_hat/sd(data[,Clicked_Left_Option])
```

```
num_obs_control <- nrow(data[Treatment==0])
num_obs_treat <- nrow(data[Treatment==1])
pwr.t2n.test(n1 = num_obs_treat, n2 = num_obs_control, d = cohens_d,
             sig.level = .05, power = NULL)
```

```
     t test power calculation

             n1 = 210
             n2 = 210
              d = 0.06706
      sig.level = 0.05
          power = 0.1053
    alternative = two.sided
```

The Cohen's D statistic is a measure of the magnitude of the difference between the mean values of the treatment group and control group. We had a Cohens' D of 0.067 which is small, and a low power of 0.1053. This is because we have a small Cohen's D and our experiment only had about 420 observations.

```r
pwr.t.test(n = NULL, d = cohens_d,  sig.level = .05, power = 0.8)
```

```
     Two-sample t test power calculation

              n = 3491
              d = 0.06706
      sig.level = 0.05
          power = 0.8
    alternative = two.sided

NOTE: n is number in *each* group
```

If we want to have higher power of 0.8, we need about 3491 observations in total when the Cohen's D does not change.

Limitations

Several limitations to our experiment can be considered. Firstly, we only analyzed the recommendation badge's effect on the picture's left side. Future studies should also consider the effect of the badge on the right side to gain a more comprehensive understanding of how positioning affects consumer choices. Secondly, our survey only included non-vegetarian people, and it would be beneficial to conduct a similar study with vegetarian choices since the population of this group is growing. Thirdly, we need more covariates for meal options, which may limit our ability to analyze the data at a user level. Finally, the images we used in our experiment do not represent the diverse range of options offered in real life, which may limit the generalizability of our findings to real-world applications.

Conclusion

In conclusion, our project aimed to examine how recommendation badges affect consumer behavior when presented with alternative options. Our survey was designed using the Qualtrics platform, where participants were assigned to answer both control and treatment questions, and randomized questions were presented. Our findings revealed that the recommendation badge on the left option does not have a significant affect on participants' choices, suggesting that appearance of food showing in pictures or other factors might have a bigger impact. On adding covariates like gender and budget per meal, there was no significant effect on the result as the ATE and standard error did not change. With a more comprehensive analysis, this project could help developers create better meal delivery apps that cater to consumer needs and preferences.

Appendix

Survey questions

Hello and welcome to our survey!

The survey is very short and will take just 1 minute to answer. Your participation in this survey is important and will help us gain insights into people's preferences while selecting meal choices.

Please select one picture from the choices provided for each meal in the survey.

Thank you for taking the time to participate in this survey!

How do you classify your diet?

- ○ Vegetarian
- ○ Non-vegetarian

Age

What is your gender identity?

- ○ Male
- ○ Female
- ○ Non-binary / third gender
- ○ Prefer not to say

How much do you usually spend while ordering a meal?
Select the choice you would prefer

- ◯ $9-$12
- ◯ $13-$16
- ◯ $17-$20
- ◯ $20+

Q2.1

Select the choice you would prefer.

Bowl 1

◯

Bowl 2

◯

Q2.2

Select the choice you would prefer.

Burger 1

◯

Burger 2

◯

Q2.3

Select the choice you would prefer.

Meatballs 1

Meatballs 2

Q2.4

Select the choice you would prefer.

Pasta 1

Pasta 2

Q2.5

Select the choice you would prefer.

Sandwich 1

○

Sandwich 2

○

Q2.6

Select the choice you would prefer.

Flatbread 1

○

Flatbread 2

○

Column information and description

Column	Description
StartDate	Start date of the survey
EndDate	End date of the survey
Progress	Progress of the survey (100 is survey completed)
Duration_In_Sec	Time it took survey to complete in seconds
ResponseId	Response id (is unique to each respondent)
If_Non-vegetarian	If they are vegetarian or Non-vegetarian
Age	Age of the respondent
Gender	Gender of the respondent
Budget_Per_Meal	Budget per meal ($13-$16, $17-$20, $20+)
Treatment	whether the question is treatment (1) or control (0)
Clicked_Left_Option	whether they selected left option (1) or right option (0)

References

HTML color codes (https://htmlcolorcodes.com)

Question Randomization (https://www.qualtrics.com/support/survey-platform/survey-module/block-options/question-randomization/)