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BA472 Course Project

Analysis of Netflix 2.0's Introductory Free Trial Test

Section 1. Introduction

Our company is **Netflix 2.0** - By Gen-Z, for Gen-Z. Our company is in the business of providing high quality curated entertainment and shows. We are an up-and-coming streaming service hoping to take the industry by storm. Given that we are a young company, we are still in the early stages, and our customers' data is one of our most valuable assets. From 2019 to 2021, our company rolled out a new free trial plan to see what would be best for our customers. We are interested in seeing how this free trial impacts customers' subscription at the end of trial. This is because we have invested a significant amount of time, money, and resources into creating our free trial offering, and it is imperative that we see if the data supports or rebuttals our research. In addition to tracking whether prospective customers converted to a full-time plan after utilizing the free trial, we have also collected information on the demographics of the customer (age, marital status, gender, etc.) and their financial habits (income, online shopper or not, etc.). We plan to incorporate this information into our research as these factors may or may not have an impact on a prospective customer's likelihood of renewing their subscription after their trial. By the end of this project, we hope to deduce the main factors that impact renewal rate, and whether or not there exists a specific demographic that our treatment is most effective for. We want to hone our offering so that it is the highest quality user experience possible, and we can only improve if we know why our audience is watching, enjoying, and subscribing to Netflix 2.0.

Section 2. Data Description & Cleaning

Our original, raw data consisted of 13 columns and 933 data points. In order to prepare our data for analysis, we applied various tools, including dropping data points with missing information, removing unnecessary columns, creating dummy variables for categorical predictors, and more:

Variable	Description	Format/Options	Notes
Date	The date of deciding whether renew or not after trial	YYYY-MM-DD	Dropped
CustomerID	Unique identifier for each customer using the streaming service.	Real Number	Dropped
CustomerAge	Age of the customer	Real Number	-
CustomerGender	Gender of the customer	Male, Female, Non-binary, Other, Prefer not to answer	-
CustomerMaritalStatus	Marital status of the customer	Single, Married, With a partner, Prefer not to answer	Converted to Binary where 'Married' and 'With a partner' = 1 and all others = 0
SubscriptionType	Type of subscription the customer tried	Basic, Premium, PremiumNoAds	-
MonthlySubscriptionCost	The cost of the subscription in $ per month	6.99, 9.99, 11.99	Converted to Pandas Numeric
DurationOfFreeTrial	Number of days for the free trial period	7, 8, 9, 10, 11, 12, 13, 14	-
HoursStreamed	Total number of hours the customer spent streaming content during the trial period	Real Number	Converted to Pandas Numeric
UserSatisfactionScore	Customer satisfaction score after trying the streaming service	1, 2, 3, 4, 5	-
RenewAfterTrial	Whether the customer renewed their subscription	Yes, No	Renamed to *Subscribed* and Converted to

	after the trial period		Binary where 'Yes' = 1 and 'No' = 0
Shops Online Or Not	Whether the customer chooses to shop online	Yes, No	Renamed to *OnlineShopper* and Converted to Binary where 'Yes' = 1 and 'No' = 0
Annual Income	Annual income of the customer in thousands	Real Number	Renamed to *AnnualIncome* and Converted to Pandas Numeric
SubscriptionTypeBinary	SubscriptionType split by the presence of or lack of ads in a plan	1, 0	Created for analysis, 'PremiumNoAds = '1' and all others = 0
CustomerGender_Female, CustomerGender_Male, CustomerGender_Non-binary, CustomerGender_Other, CustomerGender_Prefer not to say	Dummy variables of CustomerGender	1, 0	Created for analysis
AnnualIncomeBlocked	Annual Income blocked by the median value (130)	1, 0	Created for analysis, '>130' = 1 and all others = 0

Table 1 - Data Description and Modifications

After cleaning our data, we had 18 columns and 928 data points.

Section 3. Research Questions

We came up with five research questions to focus on, with the goal being extracting meaningful insights from them:

1. Does **Online Shopping** affect **Hours Streamed**?
2. Does **Subscription Type** affect **Hours Streamed**?
3. Does **Marital Status** affect **User Satisfaction Score**?
4. Does **Subscription Type** affect **Subscription Rate** ?
5. Does **Duration of Free Trial** affect **Subscription Rate**?

Research Question 1: Does **Online Shopping** affect **Hours Streamed**?

One of the most important aspects to business is understanding the tendency of our consumers. At Netflix 2.0 we felt it was important to explore this area by observing whether online shopping affects how many hours our consumers stream on the platform. Understanding this about our consumers can greatly affect how our different service tiers (basic, premium, and premium no ads) can be utilized to our advantage when targeting consumers. One of our theories is that those who shop online are more likely to be influenced by fashion trends in movies and TV shows, or by their favorite characters. With this knowledge, if a consumer who uses our platform does shop online we can use this information to position ads more effectively within our services as well as target specific consumers with specific ads. To explore this topic the research team of Netflix 2.0 came up with the following research question: "Does **Online Shopping** Affect **Hours Streamed**?"

Our team recognized the fact that this question could not be tested within a controlled environment and had to be observed naturally. After extensive data collection we used the process of DoWhy to run an extensive analysis on *HoursStreamed* as our dependent variable and *OnlineShopper* as our independent variable (descriptions above in **Section 2**). Using these variables, our team constructed a causal diagram.

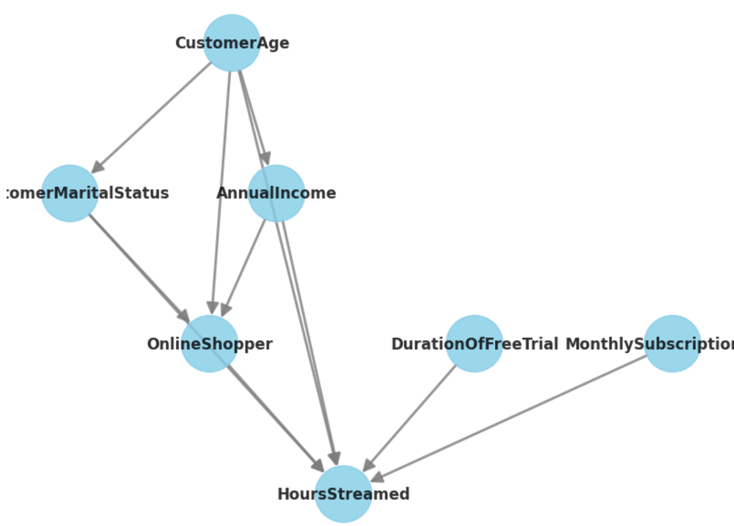

Figure 1 - DoWhy Causal Diagram

As seen in Figure 1, our team considered all possible back door path variables to ensure it was an accurate experiment. After careful consideration, we felt the variables of *CustomerAge*, *CustomerMaritalStatus*, *AnnualIncome*, *DurationOfFreeTrial*, and *MonthlySubscriptionCost*, would have an impact on either variable or both. With the causal diagram in place, our team ran three different DoWhy methods: Back Door Linear Regression, Backdoor Propensity Score Matching, and Backdoor Score Weighting.

```
BACKDOOR LINEAR REGRESSION RESULTS
Results with placebo treatment refuter:
Refute: Use a Placebo Treatment
Estimated effect:0.3596302919676475
New effect:-0.06963792476257247
p value:0.45827121720857633

Results with data subset refuter:
Refute: Use a subset of data
Estimated effect:0.3596302919676475
New effect:0.35598816757104146
p value:0.49844966923689493
```

Figure 2 - Backdoor Linear Regression Test Results

Our first method was Backdoor Linear Regression. We found significant results as seen in Figure 2 above. Looking first at our placebo treatment refuter, we observed an **estimated effect** of 0.3596 and a **new effect** of -0.0696. The new effect is close to 0 and is far from our estimated effect, therefore we can claim that our initial assumption - whether someone shops online or not *does* have an impact on streaming hours - is valid. Since our p-value is 0.458, which is less than the level of significance (alpha = 0.05), we also know that that test was unable to find a problem with our initial estimate.

We also faced positive results with our data subset refuter. The **estimated effect** of *OnlineShopper* on *HoursStreamed* was 0.359 and our **new effect** was 0.355 with a supporting p-value of 0.498. With no real difference between estimated and new effects, we concluded that our initial assumptions hold true even with a randomly selected subset of data. Our p-value was also greater than our alpha (0.05) showing us the test was unable to find any problems within our estimate. To further validate our assumptions we ran two more tests using different methods.

```
BACKDOOR PROPENSITY SCORE MATCHING RESULTS
Results with placebo treatment refuter:
Refute: Use a Placebo Treatment
Estimated effect:15.787715517241379
New effect:0.13243534482758623
p value:0.4823229276202304

Results with data subset refuter:
Refute: Use a subset of data
Estimated effect:15.787715517241379
New effect:14.916778975741243
p value:0.4134893571199838
```

Figure 3 - Back Door Propensity Score Matching Results

In Figure 3, we see positive results with a Back Door Propensity Score Matching test. The **estimated effect** came out to be 15.787 while the **new effect** came out to be 0.1324, with a p-value of 0.482 indicating statistical significance. The new effect was close to 0 and far from the estimated effect value, giving us evidence in support of our initial assumptions.

When looking at the data subset refuter we get an **estimated effect** of 15.78 and a **new effect** of 14.916 with a p-value of 0.413. These results are also positive, as the estimated effect and new effect are close in results, further supporting our initial assumptions, and the p-value is greater than 0.05, hence there was no issue within the results.

```
BACKDOOR PROPENSITY SCORE WEIGHTING RESULTS
Results with placebo treatment refuter:
Refute: Use a Placebo Treatment
Estimated effect:0.7616610269645818
New effect:-0.3441843245391073
p value:0.38134355113744234

Results with data subset refuter:
Refute: Use a subset of data
Estimated effect:0.7616610269645818
New effect:1.047495062880353
p value:0.25722573450943687
```

Figure 4 - Back Door Propensity Score Weighting Results

Our third and last test we ran with DoWhy was Back Door Propensity Score Weighting. The results with this method also supported our assumptions. Referring to Figure 4, after running the test the **estimated effect** was 0.761 and the **new effect** was -0.344 with a p-value of 0.381. Although the estimated effect and new effect are not extremely far apart, we can still say that our assumptions hold true as the new effect is close to 0 and somewhat far from the estimated effect. Our p-value is above 0.05, so again we can conclude that there was no issue found with the significance of the results.

When looking at the data subset refuter test, our **estimated effect** came out to be 0.761 and the **new effect** came out to be 1.047, and a p-value of 0.257. Our estimated and new effects are not as close when compared to the first two tests, however they are close enough in range to support our assumptions, and the p-value being greater than 0.05 leads us to conclude that the test found no issue within our results.

After running the three DoWhy tests we felt that we could make a valid argument that whether a consumer partakes in online shopping did have an impact on the number of hours streamed. Netflix 2.0 could grow and benefit from utilizing this conclusion in our potential advertisement strategies. By focusing on using Google Analytics and Facebook advertising as marketing venues, we can better reach online shoppers who stream more and make them aware of our platform. Our results give us confidence in building a revenue stream that focuses around online shoppers to keep them entertained within the streaming platform with a mixed strategies of content and advertisements to always keep them engaged.

Research Question 2: Does **Subscription Type** affect **Hours Streamed** (controlling for **Annual Income**)?

It is critical for Netflix 2.0 to understand the factors that influence user engagement in an increasingly competitive digital streaming marketplace. We decided to investigate the number of hours users spent on our trial streaming content and looked at it as an important engagement metric. Another variable, subscription type, is an important measurement for our expected revenue for customers that chose to renew. Understanding how the three different plans offered affect the usage of our service helps inform pricing strategies and plan features. In theory, the type of subscription plan should influence streaming behavior, with premium plans potentially leading to more hours streamed due to benefits such as ad-free viewing.

To explore this hypothesis, we asked, “Does **Subscription Type** Affect **Hours Streamed**?” We used a linear regression analysis to answer this question, with *HoursStreamed* as the dependent variable and *MonthlySubscriptionCost* as the independent variable. The *MonthlySubscriptionCost* column represents the cost of various subscription types, including Basic, Premium, and Premium with No Ads. In addition to that, we controlled for **Annual Income** to eliminate potential income-related biases that could confound the results and ensure the accuracy of our findings.

```
==============================================================================
Dep. Variable:           HoursStreamed   R-squared:                       0.001
Model:                             OLS   Adj. R-squared:                 -0.002
Method:                  Least Squares   F-statistic:                    0.2695
Date:                 Mon, 04 Dec 2023   Prob (F-statistic):              0.764
Time:                         15:09:12   Log-Likelihood:                -3803.6
No. Observations:                  928   AIC:                             7613.
Df Residuals:                      925   BIC:                             7628.
Df Model:                            2
Covariance Type:             nonrobust
==========================================================================================
                             coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------------------
const                     38.3022      2.759     13.880      0.000      32.887      43.718
MonthlySubscriptionCost   -0.1488      0.232     -0.640      0.522      -0.605       0.307
AnnualIncome              -0.0043      0.012     -0.364      0.716      -0.028       0.019
==============================================================================
Omnibus:                        55.685   Durbin-Watson:                   2.036
Prob(Omnibus):                   0.000   Jarque-Bera (JB):               49.509
Skew:                            0.498   Prob(JB):                     1.78e-11
Kurtosis:                        2.462   Cond. No.                         780.
==============================================================================
```

Figure 1 - OLS Regression Results of Hours Streamed and Monthly Subscription Cost

From Figure 1, the regression results surprisingly suggest that there is no statistically significant relationship between the ‘MonthlySubscriptionCost’ and ‘HourStreamed.’ The p-value associated with ‘MonthlySubscriptionCost’ is 0.522, greater than the chosen alpha of 0.05. This indicates that the three different subscription types do not significantly affect the number of hours streamed. Furthermore, the control variable ‘Annual Income’ also did not show a significant relationship with ‘HoursStreamed, ' as the associated p-value was 0.716.

In order to better understand the dynamics of user engagement, we narrowed our focus to a more specific aspect of streaming service subscriptions: Advertisements vs No Advertisements. So in our second pursuit, we converted the variable into a binary variable, ‘SubscriptionTypeBinary,’ to differentiate between Trials with ads (coded as 0) and without ads (coded as 1). This pivot allowed us to assess the impact of ad-free viewing on streaming behavior directly. We incorporated ‘AnnualIncomeBlocked’ as a conditioned variable, accounting for different income levels in a blocked fashion. Annual Income was blocked at $130,000 as this was the median income of our dataset, providing a clear distinction between lower and higher income segments.

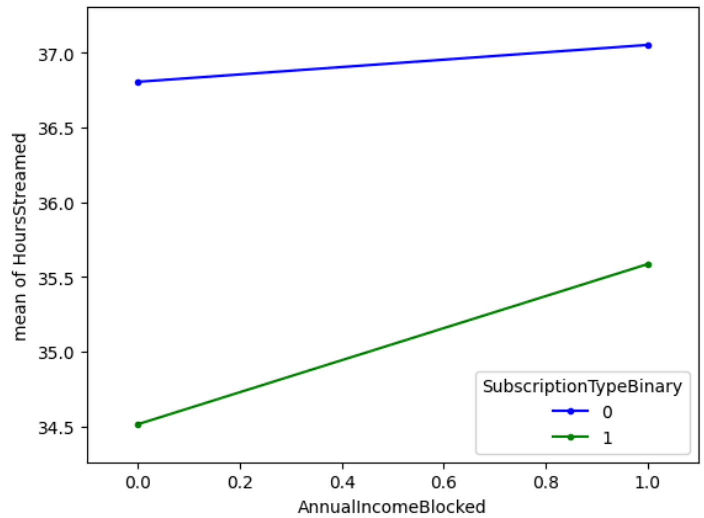

Figure 2 - Interaction Plot of HoursStreamed and SubscritionTypeBinary, with AnnualIncomeBlocked

From Figure 2, we can see the interaction plot visually representing the relationship between 'SubscriptionTypeBinary,' 'AnnualIncomeBlocked,' and 'HoursStreamed.' The green slope for ad-free subscriptions indicates that as income increased, so did the number of hours streamed by approximately 1 hour. However, for ad-supported subscriptions, income level has little to no effect on streaming hours. The interaction plot suggests that there could be potential for interaction; therefore, we conducted the ANOVA analysis shown in Figure 3 to evaluate the presence of an interaction numerically.

	df	sum_sq	mean_sq	F	PR(>F)
C(SubscriptionTypeBinary)	1.0	716.316540	716.316540	3.366424	0.066859
C(AnnualIncomeBlocked)	1.0	61.956835	61.956835	0.291174	0.589599
C(SubscriptionTypeBinary):C(AnnualIncomeBlocked)	1.0	34.718179	34.718179	0.163163	0.686355
Residual	924.0	196611.129136	212.782607	NaN	NaN

Figure 3 - ANOVA Analysis

Despite the visual indication of a potential interaction in the plotted data, the ANOVA results did not confirm this. The analysis concluded that there is no relationship between both SubscritionTypeBinary and AnnualIncomeBlocked with HoursStreamed, as all p-values eclipsed our chosen alpha of 0.05. Additionally, the interaction between SubscritionTypeBinary and Income has no significant impact on the hours streamed as the F-statistic yielded 0.686, greater than the conventional threshold of 0.05.

The different subscriptions do not affect streaming hours significantly. It would be more beneficial to focus on enhancing the quality variety of content to increase user engagement. Additionally, if higher-priced subscription tiers differ in terms of hours streamed, offering a unified subscription type could simplify users' choices and differentiate the service in the competitive market.

Research Question 3:Does **Marital Status** Affect **User Satisfaction Score**?

Netflix 2.0 was founded with the idea of targeting younger generations, rather than having a broad catalog that would appease the mass population. Our goal was to create a selection aligned with Gen-Z tastes, and to capture a large percentage of the Gen-Z population as subscribers. After conducting the trial, we decided to look for trends in the demographics of our trial users. We wanted to know how a customer's marital status would affect their personal satisfaction score. We did this to see if we had reached the correct demographic, as those who are younger have a much higher chance of never being married or being with a long term partner. In addition to this, we wanted to explore if those younger customers that **were** married or in a relationship enjoyed our platform more or less than those who were single during the trial.

To answer these questions, we ran a linear regression on User Satisfaction Score, a continuous value from three to five, using a dummy coded version of Marital Status: if a customer was Married or With a Partner, the variable=1, otherwise customers had values of 0. To ensure we had interpretable results without any confounding demographic variables, we controlled for Customer Age, as well as for Gender. We created four dummy variables to encapsulate the four responses for Gender: Male, Female, Non-Binary, and Other. The results can be found below, in Figure 4:

```
                            OLS Regression Results
==============================================================================
Dep. Variable:     UserSatisfactionScore   R-squared:                       0.005
Model:                               OLS   Adj. R-squared:                 -0.001
Method:                    Least Squares   F-statistic:                    0.8035
Date:                   Mon, 04 Dec 2023   Prob (F-statistic):              0.567
Time:                           13:01:24   Log-Likelihood:                -828.33
No. Observations:                    928   AIC:                             1671.
Df Residuals:                        921   BIC:                             1704.
Df Model:                              6
Covariance Type:               nonrobust
==========================================================================================
                                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------------------
const                          4.4420      0.071     62.671      0.000       4.303       4.581
CustomerMaritalStatus          0.0517      0.039      1.326      0.185      -0.025       0.128
CustomerAge                   -0.0019      0.001     -1.542      0.123      -0.004       0.001
CustomerGender_Female         -0.0317      0.061     -0.517      0.606      -0.152       0.089
CustomerGender_Male            0.0182      0.061      0.298      0.766      -0.102       0.138
CustomerGender_Non-binary      0.0061      0.060      0.102      0.919      -0.112       0.124
CustomerGender_Other           0.0019      0.061      0.031      0.976      -0.118       0.122
==============================================================================
Omnibus:                      102.229   Durbin-Watson:                   2.044
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               91.859
Skew:                          -0.695   Prob(JB):                     1.13e-20
Kurtosis:                       2.335   Cond. No.                         251.
==============================================================================
```

Figure 4 - Linear Regression Predicting User Satisfaction Score with Marital Status, Controlling for Gender and Age

After running our regression, we found several takeaways about User Satisfaction Score, Marital Status, Age, and Gender:

1. Our trial service yielded high user satisfaction, with an average base coefficient of 4.44 on a scale of three to five. The coefficient is coupled with a p-value of 0.000, meaning significance at $\alpha=0.05$. This means our product is well liked by all manner of customers, regardless of demographic.
2. Marital status, at least whether or not a customer is in a relationship, does not significantly impact their satisfaction with our trial service. At $\alpha = 0.05$, the p-value of 0.185 is too large to claim any sort of significance.
3. Age does not have a significant effect on a customer's satisfaction with our trial service at $\alpha=0.05$ or even $\alpha=0.10$ (p-value = 0.123).
4. Gender is not a significant factor in how much a customer enjoys our trial service, with all four categories' p-values greater than 0.60.

These findings lead us to the conclusion that we have failed in refining a user experience tailored to Gen-Z audiences, but we have crafted a high quality experience for a wide range of demographics. From this research, we have to make a decision based on these and other findings about whether or not we want to change our current offerings to exclusively appeal to Gen-Z audiences, even though Gen-Z audiences **and** other demographics (families, millennials, grandparents, etc.) enjoy our current platform, at least when it comes to the free trial. This analysis has shown we have a high quality product, and how we tailor it may affect perceived quality and user satisfaction.

Research Question 4: Does **Subscription Type** affect **Subscription Rate**?

In a digital world where subscription services have account tiers, it is imperative for Netflix 2.0 to price their plans correctly. By ensuring that each account type costs a fair amount for its features, Netflix 2.0 hopes to understand and optimize their subscription renewal rate. Specifically, since Netflix 2.0's ethos is centered around the Gen-Z customer, the company was interested in how the presence of or lack of advertisements in an account impacted a customer's likelihood to resubscribe. For this analysis, we utilized an A/B test with blocking by account type (advertisements versus no advertisements).

Our null and alternative hypotheses for this test were as follows:

- H_0: There is no difference in the conversion rates between accounts that have ads (Basic and Premium) and accounts that don't have ads (Premium with No Ads)
- H_A: There is a difference in the conversion rates between accounts that have ads (Basic and Premium) and accounts that don't have ads (Premium with No Ads)

In this analysis, we deduced the conversion rates, and the p-values from a proportions z-test and a Chi-Square test, to come to a conclusion. Our results were as followed:

```
Conversion rate of no ads trial period: 0.6480263157894737
Conversion rate of ads trial period: 0.6522435897435898
Proportions z-test p-value: 0.8993468949095398
Chi-squared test p-value: 0.9576328717573851
```

Figure 5 - Code Output for Subscription Renewal Rates and P-Values (Subscription Type)

Based on Figure 5, we see that the conversion rates for accounts with ads, and for accounts without ads, were almost identical (0.652 and 0.648, respectively). Additionally, the P-value for both the Proportions z-test ($p = 0.899$) and the Chi-squared test ($p = 0.957$) significantly exceed the level of significance (0.05). Therefore, Netflix 2.0 found that this test was insignificant, meaning that subscription type likely does not have an impact on subscription renewal rate. With this newfound knowledge, additional testing with a more diverse separation between ad-inclusive and ad-exclusive accounts may yield better insights into future plan offers for Netflix 2.0. Regardless, this A/B test fails to reject the null hypothesis, in that there is no evidence to suggest that subscription type impacts renewal rate.

<u>Research Question 5: Does **Duration of Free Trial** Affect **Subscription Renewal Rate**?</u>

Netflix 2.0 also wanted to explore whether the duration of our free trial offerings would affect user subscription renewal rate. By answering this question, we hope to identify the optimal trial length that would increase the likelihood of converting trial users into paying customers. In the long run, by converting trial users to long-term subscribers, we could potentially increase our customer lifetime value.

Our group decided to conduct an A/B test, as we do not have traditional control vs. treatment groups. Instead, we will have one group receive less than 10 days of free trial (our 'short' offering, which can be considered as the A group) while another group would receive greater than or equal to 10 days of free trial (our 'long' offering, which can be considered as the B group). This 10 day threshold is calculated by taking the mean of our free trial durations. The key performance indicator would be the subscription renewal rate. The renewal rate represents the percentage of our streaming site users that renew their subscription.

Our team constructed the null hypothesis (H_0), which states that adding a longer trial period *does not change* the subscription renewal rate compared to our shorter trial period. For the alternative hypothesis (H_a), it states that adding a longer trial period *does change* the subscription renewal rate compared to our shorter trial period. After formulating these hypotheses, we calculated the subscription renewal rates for each corresponding group and the p-values from a proportions z-test and chi-squared test.

```
Subscription renewal rate of short trial (< 10 days) period: 0.53
Subscription renewal rate of long trial (>= 10 days) period: 0.73
Proportions z-test p-value: 1.1703261822899281e-09
Chi-squared test p-value: 1.8153283099004142e-09
```

Figure 6: Code Output for Subscription Renewal Rates and P-values (Duration of Free Trials)

Based on our results from Figure 6, the p-values for both the proportions z-test and chi-squared test are notably less than our significance level (α) at 0.05. Therefore, we can reject the null hypothesis and conclude that adding a longer trial period changes the subscription renewal rate. More specifically, our team decided to go with the longer trial period as it has a higher subscription renewal rate of 73%

compared to the shorter trial period, which only has a subscription renewal rate of 53%. As of now, the longest duration of free trials that Netflix 2.0 is offering is only 14 days, which is typically the standard for most streaming companies. In the future, we hope to experiment further and determine whether trial periods as long as 30 days may improve subscription renewal rates.

Section 4. Conclusion

Netflix 2.0's Introductory Free Trial Test was an extensive analysis of customers' streaming behaviors, with the goal of extracting valuable information on how to better position the business and its offerings. Our five research questions explored multiple potential relationships, centered on customers' online shopping behaviors, number of hours streamed, subscription type, marital status, free trial durations, and subscription renewal rate. Specifically our experiments explored the following relationships and deduced the following results:

1) Our assumptions that **Online Shopping** has an impact on **Hours Streamed** were valid, evidenced by a DoWhy analysis including a causal diagram and several tests.
2) Different **Subscription Types** do not have an impact on **Hours Streamed**, evidenced by multiple regression analyses and an interaction plot.
3) A **Customer's Marital Status** does not impact **User Satisfaction Score**, evidenced by a multiple regression analysis.
4) Different **Subscription Types** do not have an impact on **Subscription Rate**, evidenced by an A/B test including conversion rates, a proportions z-test, and a chi-square test.
5) A **Longer Free Trial Duration** does have an impact on **Subscription Rate**, evidenced by an A/B test including conversion rates.

Our analysis covered a plethora of angles, assessing the effectiveness of various factors and making observations for future experiments and product implementations. Among all our findings, there were two results that provided the most useful business insights. The first was that different subscription types did not have an impact on subscription rate. This surprised us, as Netflix 2.0 expected that users with an account that did not have ads (Premium with No Ads) should've had a higher conversion rate since consumers are typically most affected by advertisements. In the future, we'd want to conduct this test again with more data to ensure our results in this report are repeatable at different scales. We also learned that customers who experienced a longer free trial were more likely to subscribe. In our experiment, a longer free trial equates to 10-14 days. In the future, we would like to test whether our next implementing a longer free trial - up to 30 days - continues to translate to more subscribers. In summary, our researchers at Netflix 2.0 extracted valuable information regarding our business, customers, and recent free trial experiment. It is clear that more data and more testing is required in order to offer more concrete evidence for business decisions. However, working within the constraints of the available data, we were still able to deduce potential improvements to our business in the fields of marketing, demographic shifts, and optimal trial strategies.