KyngaCell: Analysis of Nicht-Soporific's New Online Community Feature

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Executive Summary

To address KyngaCell's concerns about the effects of a new feature of its game Nicht-Soporific, we perform tests to check its effects on revenue, retention, and customer lifetime value (CLV). Our results show an increase in retention and CLV, though a reduction in retention with higher churn rates. We also found that organic entry into the game was not a useful factor in predicting churn. We note limitations of the study and make recommendations both for further analysis and business, such as increasing the period of data and additional variables, conducting behavioral analysis, and measuring engagement for better strategies for KyngaCell's users.

Introduction

Mobile gaming company KyngaCell executives are interested in whether a new online community feature in their game, Nicht-Soporific, has improved user revenue and retention. Our objective is to examine whether the feature has affected the average spend, retention, and CLV, as well as explore the usage of a new variable: user's method of joining the game .

Problem Formulation

To observe whether there was a revenue increase, we tested the difference in the short-term spending increase of the users that joined and did not join through a wilcoxon rank sum test and a linear regression model for the change in spending and the online community. For retention, we built a logistic regression model to predict churn with relevant churn data provided by the gaming team. For CLV, we computed CLV per customer and conducted a t-test to determine whether average CLV was higher in users that joined the online community. We also built a linear regression model on computed CLV to observe the relationship and get an idea of the magnitude of average CLV difference brought about by joining. Lastly, given additional data, we checked whether the method of joining the game has any effect on player churn.

Data Description

The gaming team provided us a sample with the following data: whether users joined the online community, spend before and after joining, whether the customer churned at 3 months, their average monthly spend in their last three months, and whether they joined the game organically or through the firm's campaign. The dataset contains a sample of 199 customers, from both control (did not join the online community) and test (joined the online community) groups.

In the QWE Inc. example of predicting customer churn, Ovchinnikov (2013) stated the analyst consulted with the company's vice president of customer services for intuition on identifying relevant variables. For the churn model, we consider the online community, age, and average spend from the Data 2 set provided by the gaming team. Online community is necessary as the main subject of this study. Player's age may indicate game fatigue or loyalty. Spend may be a factor in a player's decision to quit if the spend for game progress goes beyond their personal thresholds or indicate how dedicated the player is to the game. We do not have further game information (degrees of payment, subscriptions, availability of in-game items through social vs purchase methods, etc.) to make any other prima facie inferences.

We computed CLV, shown in Appendix D using the overall retention rate (r), average spend of each customer as our margin base (m) at 50%, and we assume acquisition costs to be zero. Average lifetime of the customer was calculated at 1.69 periods, so we set *t* at 2 (rounded up). As discount rates often vary among companies and industries, we use a discount rate (i) of 6.5%, which is the discount rate used by other major mobile gaming companies such as Activision Blizzard, Inc. (5Y DCF Growth Exit for Activision Blizzard, n.d.).

In Data 3, we are provided with information on whether the customer joined the game through a campaign effort of the firm or through organic means, which may be an indicator of:

1. Effectivity of paid versus "organic" marketing strategies of the firm (Grguric, 2021)
2. A player's authentic interest in the game which may affect likelihood of staying

As we have no information on the marketing strategies of the firm, we use this as an additional variable in the regression model for churn to determine whether it affects player retention.

Model Development, Estimation, and Results

Tests conducted for revenue effect are detailed in **Appendix A**. The Wilcoxon Rank Sum Test indicated that average spending increased at a greater magnitude for those that joined the online community than those that did not. We have the following linear regression model:

$$y = 30.872 + 29.018x_1$$

Where y is the change in spending and x_1 is whether they joined the online community. Without joining the online community, the average spending increase for a particular user was $30.87. An additional $29.02 to their average spend can be observed if they joined, giving an idea of the magnitude of potential increase in user revenue. However, we note that while both tests indicate higher increase in spend for those that joined, this analysis is based on short term data and might not be reliable for longer period analysis given other factors that could affect spending.

The logistic regression model for churn and predictions can be seen in **Appendix B** and **Appendix C** where we find that joining the online community actually increased player churn. The logistic regression model is:

$$y = 0.462 + 0.918x_1 - 0.052x_2 - 0.003x_3$$

Where y is churn, x_1 is joining the online community, x_2 is player firm age, and x_3 is average spend in the last three months of life with the firm. Age and spend do not appear to be significant. Joining the online community was significant and has a positive intercept, agreeing with sample proportions that suggest an increase in churn rate for those that joined. The AIC from this model was 268.54, lower than the model regressing churn with only the online community variable, which yielded an AIC of 280.16.

The computation for CLV, t-test, and the related regression model with the online community are shown in **Appendix D**. The t-test shows that the average CLV of those who joined was higher than those who did not join. The regression model for CLV and the online community is:

$$y = ß_0 + ß_1x_1$$

Where y is CLV and x_1 is joining the online community. In the absence of the online community feature, the average CLV (per customer) was $46.65. The regression provides us with an idea of the magnitude of change in CLV, where for a particular user, an additional $21.55 to their CLV can be observed if they join the online community. Overall, we observe that the online community feature appears to spike revenue in the short term, which given the shorter average lifetime, appears to show higher CLV despite the lower retention due to the three-month churn.

We look at whether the campaign variable is a useful predictor for churn in Appendix E, by adding it as a variable into the logistic regression model for churn:

$$y = 0.356 + 0.930x_1 - 0.052x_2 - 0.003x_3 + 0.180x_4$$

Where the additional variable x_4 represents whether the player joined through a campaign or organically. Again, we can infer that firm age and average spend are insignificant. We also see no significant relationship between churn and the campaign variable. Additionally, the AIC of this model is 270.19, suggesting that campaign may not be worthwhile to include to predict churn.

Recommendations and Managerial Implications

Drachen et. al. (2018) published research which found that online social interactions have no significant effect on players' purchase behaviors, which in turn had limited effect on their CLV. In our analysis, we found that while the online community appears to result in a short-term increase in revenue, it also reduces retention with higher churn rates for those that joined. Gupta et. al. (2004) found in their study on customer valuation that retention had a higher impact on CLV, which suggests that companies should focus on increasing retention.

A limitation of this analysis is the lack of data to the time period. Having a longer period, e.g. more months, would allow for more comprehensive results and more meaningful interpretations. This could make for better inferences in making recommendations for business. Furthermore, socioeconomic information like geographic and other player demographic data would allow for a more meaningful analysis. This could isolate other potential factors that are relating to not having statistical significance in the variable that has organic/campaign. Overall having more variables relating to the individual and across time would improve findings of churn and revenue of the business.

In order to retain the online customers, the business needs to create a unified version of all the data manually which is very time-consuming. Oftentimes it’s also very error-prone and does not allow for real-time ad-hoc analysis. To see the complete picture of your business, the business would need all data in one place: a data warehouse optimized for behavioral analysis. To understand the loyal players, behavioural analysis can be used. Finding what gamers like best in the game comes down to one question: what do they find to be the most fun? Measuring fun objectively using behavioral analysis allows analysts to leverage some great insights about what keeps your players coming back for more. The fun factor, as it can be described, can be used to assess engagement to get a quantitative measure of how many players are enjoying a specific feature of the game. For instance, if a player is constantly getting stuck at a particular level or point in the game, then the player cannot be considered as having much fun. Figuring out what could help you measure the “fun meter” is key to finding a way of optimizing KyngaCell’s retention strategy. The fun meters could be tied to in-game currency, time spent playing a certain mode or level, or it could be associated with user feedback that the company is getting from its user base. At the end of the day, how to measure “fun” will depend on the functionality of the game. An introduction of a measure like Fun Score could be used to track engagement of the players by a combination of how many times a week someone plays the game, for how long, and how active they are in it. With this Fun Score at hand, KyngaCell could use predictive analytics to understand what their most valuable players have in common, what players are at risk of churning, what behavior precedes churn, etc. This helps them re-engage players at risk before it is too late, and focus on the acquisition and engagement strategies that bring in the players with the highest lifetime value.

Another consideration is targeting the right audience by cross-referencing the engagement results of the customers from the data collected which will provide insight on whether we are targeting the right customers. Giving the users a chance to interact with each other is another point where gamers can enjoy their time while gaming but maintaining the sanctity of the engagement meaning keeping the gaming environment non hostile and a comfortable zone for having fun. Additionally increasing the game virality would lead to exposing the game portal to a lot of potential customers by engaging in social media activities, sharing posts, allowing the customers an opportunity to increase their social capital as well as creating common communities and groups with similar interests.

Conclusion

Our tests resulted in the following findings: that the online community increased revenue and CLV but it reduced retention of players. The new variable, campaign/organic, was not a useful predictor for churn. Overall, the study is limited by the timeframe of the data provided, and further insights could be gained by expanding the analysis through inclusion of other potentially relevant (e.g.) variables such as player demographic over a longer period of time. We also recommend the use of behavioral analytics and examining user behavior (e.g. creating measurements of engagement) against facets of the game to form better business strategy to improve retention and value in the future.

References

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Appendix

Appendix A: Testing Increased User Revenue

Data 1 provided us with information on the spend of the game players a month before and a month after the introduction of the online community feature in the game Nicht-Soporific. As we want to determine impact on user revenue, we calculate the Change in User Spend for each group by getting the difference between the months before and after the introduction of the feature. We then compare average change in user spend between populations to determine whether there was a greater increase in one group over another. We conduct a wilcoxon rank sum test (due to the non-normality of the data from testing) and build a linear regression model.

<u>Test 1: Wilcoxon Rank Sum Test</u>

The population definition, hypotheses, and test results are as follows:

Population:

- Population 0: those who did not join the online community (control)
- Population 1: those who joined the online community (test)

Hypothesis:

- H_0: Population locations are the same (no difference in spend)
- H_1: Population 0 is to the left of population 1 (average increase higher for those who joined the online community than those who did not)

Results:

```
        Wilcoxon rank sum test with continuity correction

data:  SpendChange by OnlineComm
W = 8, p-value < 2.2e-16
alternative hypothesis: true location shift is less than 0
```

We conclude that in the month after the feature was implemented, average spending increased more for those that joined the online community than those that did not.

Test 2: Linear Regression

We also check using a linear regression, given that our dependent variable is continuous (change in spend) and our independent variable is categorical (joined/did not join).

$$y = ß_0 + ß_1 x_1$$

Where:

y = spending increase

x_1 = joining the online community

```
Call:
lm(formula = SpendChange ~ OnlineComm)

Residuals:
     Min       1Q   Median       3Q      Max 
-15.8718  -7.8810   0.1098   7.1282  15.1098 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept)   30.872      0.830   37.20   <2e-16 ***
OnlineComm    29.018      1.293   22.44   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 8.977 on 197 degrees of freedom
Multiple R-squared:  0.7189,    Adjusted R-squared:  0.7174 
F-statistic: 503.7 on 1 and 197 DF,  p-value: < 2.2e-16
```

The linear regression model: $y = 30.872 + 29.018x_1$

The overall model is statistically significant based on the global F-test. The intercept of 30.872 and the online community are both highly statistically significant. We see here that in the absence of the online community feature, the average spending increase was $30.87, which is also the mean of the change in spending of the control group.

The linear regression provides us with an idea of the magnitude of change in user revenue provided by the online community feature, where for a particular user, an additional $29.02 to their average spend can be observed.

We see that both tests indicate that joining the online community has increased average user spend at a greater magnitude. This informs us and the team at KyngaCell that the community feature does increase company revenue. We note, however, that this is short-term and only in the immediate month after, which may not be a reliable measure if the team wants long-term revenue effects from the online community feature.

Appendix B: Retention and Churn: Logistic Regression Model Estimation

Data 2 provided us with variables that potentially have an effect on retention. Apart from identifying control and test groups, the gaming team provided information on the player's age at the firm after the launch of the feature, their average spend in their last three months (90 days) at the game, and whether or not they churned after those three months (90 days).

At a glance

Sample	**Total**	**Churned**	**Rate - Churn**	**Rate - Retention**
Joined	82	58	70.73%	29.27%
Did not join	117	60	51.28%	48.72%

At a first glance into the sample provided, it would appear that the churn rate is higher for those that joined the online community. We build a logistic regression model for churn to observe whether joining the online community (and other variables presented) have a statistically significant relationship with churn, and in turn, the retention of the players.

Churn Regression Model

In the QWE Inc. example of predicting customer churn, Ovchinnikov (2013) mentioned that in the analyst's data collection and building of the model for QWE, the analyst consulted with the QWE Inc.'s vice president of customer services to use existing knowledge and intuition on identifying possible relevant characteristics. The three variables presented in Data 2 are all relevant candidates for predicting customer churn. The online community variable is necessary as the main subject of this study, but we also look at the player's firm age and average spend as relevant factors. Player's age in the game may show either game fatigue or loyalty. Increasing spend may be a relevant factor in a player's decision to quit if the spend necessary for their game progress goes beyond their personal thresholds. We do not have further game information to make any other prima facie inferences, such as whether the game is free to play or pay to play, whether playing requires subscriptions, if in-game currency or items are available in the game through social vs purchase methods, etc..

We build the model using a logistic regression utilizing all three independent variables:

$$y = ß_0 + ß_1x_1 - ß_2x_2 - ß_3x_3$$

Where:

y = churn

x_1 = joining the online community

x_2 = customer age with the firm after launch of online community

x_3 = average spend in the last/latest three months of life with the firm

```
Call:
glm(formula = Churn ~ OnlineComm + FirmAge + AveSpend, family = binomial(link = "logit"),
    data = Data3)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.6641  -1.2094   0.8045   1.1049   1.2815

Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept)  0.462435   0.535488   0.864  0.38782
OnlineComm   0.917627   0.355216   2.583  0.00979 **
FirmAge     -0.051796   0.073144  -0.708  0.47886
AveSpend    -0.002899   0.005657  -0.512  0.60836
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 268.95  on 198  degrees of freedom
Residual deviance: 260.54  on 195  degrees of freedom
AIC: 268.54

Number of Fisher Scoring iterations: 4
```

The logistic regression model: $y = 0.462 + 0.918x_1 - 0.052x_2 - 0.003x_3$

The p-values do not indicate confidence in firm age and average spend having an effect on churn, though we see that the p-value for joining the online community is statistically significant.

The following are the exponentiated coefficients:

Intercept	Online Community	Firm Age	Average Spend
1.5879361	2.5033417	0.9495225	0.9971055

The confidence intervals of the exponentiated coefficients are as follows:

	2.5%	97.5%
Intercept	0.5579837	4.591283
Online Community	1.2611151	5.100114
Firm Age	0.8221310	1.096154
Average Spend	0.9860294	1.008210

The positive coefficient indicates that holding all else equal, those that joined the online community may be more likely to churn than their counterparts who did not join the online community.

The AIC of this model is 268.5374. For robustness checks, we ran the model regressing churn with only the online community variable, as shown in the attached R file, though this yielded an AIC of 280.1603.

We obtain the following confusion matrix:

```
             Actual 1 Actual 0 Total
Predicted 1       100       56   156
Predicted 0        18       25    43
Total             118       81   199
```

From the confusion matrix we see that using our churn logistic regression model, we see that there is an overestimation of predicted churn (156 predicted vs 118 actual) and an underestimation of those who did not churn (43 predicted vs 81 actual). The manually calculated accuracy of the predictive model is 62.81%.

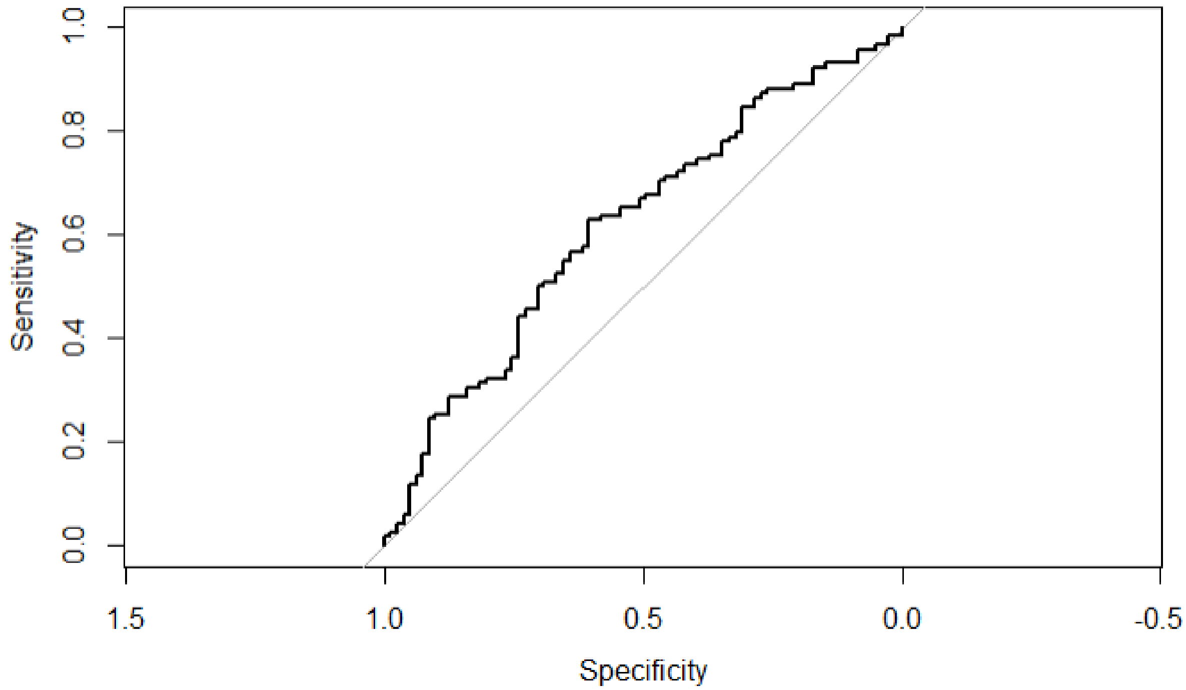
The R file submitted includes the final Data 2 table containing the sample sample of players and their corresponding information, with additional columns predicting their probability of churn using the model, and based on that probability, predictions on the user churning. We also note whether they were misclassed when compared with the actual data. A sample is as follows:

	Customer ID	Joined?	Customer Age with Firm at time of launching the online community	Churned at 3 months after launch of the online community	Average Spend Last 3 months of Life with the firm	prob_churn	pred_churn	missclass
1	1000201	1	7.008895	0	88.00000	0.6817756	1	TRUE
2	1000202	0	6.595568	1	102.66667	0.4559177	0	TRUE
3	1000203	0	7.932284	1	45.33333	0.4800524	0	TRUE
4	1000204	1	2.391398	1	113.33333	0.7166040	1	FALSE
5	1000205	1	5.335660	0	99.33333	0.6933353	1	TRUE
6	1000206	1	3.437049	1	68.00000	0.7320258	1	FALSE
7	1000207	1	4.869794	0	86.00000	0.7065192	1	TRUE
8	1000208	0	7.669013	1	58.00000	0.4742943	0	TRUE
9	1000209	0	6.833738	0	106.00000	0.4504663	0	FALSE
10	1000210	1	5.361552	1	50.00000	0.7226049	1	FALSE

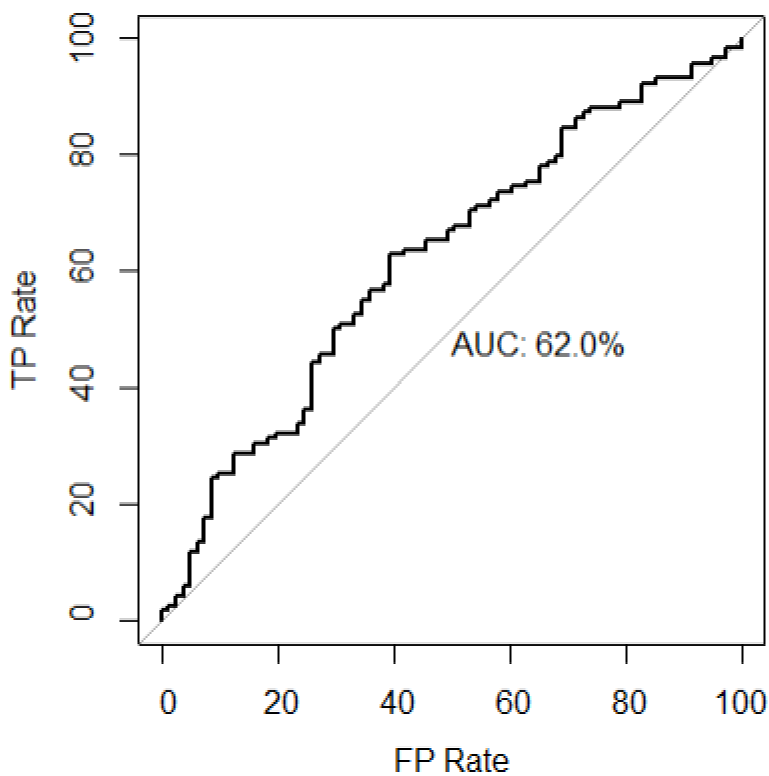
Appendix C: Confusion matrix and statistics

```
Confusion Matrix and Statistics

          Reference
Prediction   0   1
         0  25  18
         1  56 100

               Accuracy : 0.6281
                 95% CI : (0.557, 0.6954)
    No Information Rate : 0.593
    P-Value [Acc > NIR] : 0.1743

                  Kappa : 0.1685

 Mcnemar's Test P-Value : 1.699e-05

            Sensitivity : 0.8475
            Specificity : 0.3086
         Pos Pred Value : 0.6410
         Neg Pred Value : 0.5814
             Prevalence : 0.5930
         Detection Rate : 0.5025
   Detection Prevalence : 0.7839
      Balanced Accuracy : 0.5780

       'Positive' Class : 1

Setting levels: control = 0, case = 1
Setting direction: controls < cases
```

```
Call:
roc.default(response = Data2$`Churned at 3 months after launch of the online
community`,     predictor = ChurnLogit$fitted.values, plot = TRUE)

Data: ChurnLogit$fitted.values in 81 controls (Data2$`Churned at 3 months after
launch of the online community` 0) < 118 cases (Data2$`Churned at 3 months after
launch of the online community` 1).
Area under the curve: 0.6196
Setting levels: control = 0, case = 1
Setting direction: controls < cases

Call:
roc.default(response = Data2$`Churned at 3 months after launch of the online
community`,     predictor = ChurnLogit$fitted.values, percent = TRUE, plot = TRUE,
legacy.axes = TRUE, xlab = "FP Rate", ylab = "TP Rate", print.auc = TRUE)

Data: ChurnLogit$fitted.values in 81 controls (Data2$`Churned at 3 months after
launch of the online community` 0) < 118 cases (Data2$`Churned at 3 months after
launch of the online community` 1).
Area under the curve: 61.96%
```



Sensitivity
0.0
0.2
0.4
0.6
0.8
1.0
1.5
1.0
0.5
0.0
-0.5
Specificity



TP Rate
0
20
40
60
80
100
AUC: 62.0%
FP Rate

Appendix D: CLV Computation

We computed CLV using the following standard formula:

$$CLV = \sum_{t=1}^{T} \frac{mr^{t-1}}{(1+i)^{t-1}} - AC$$

We use the average spend of each customer as our margin (*m*), at 50% of customer spend. Based on Data 2 provided, we know that 118 out of a total 199 players in the sample churned after three months, giving us an overall churn rate of 59.3% and an overall retention rate (*r*) of 40.7%. Average lifetime of the customer was calculated at 1/(1-0.407) or 1.69 periods. We set periods (*t*) to 2, rounding up from 1.69 to limit the periods for calculation of CLV. Discount rates vary among companies and industries, so since KyngaCell is in mobile gaming, we use a discount rate (*i*) of 6.5%, which is the discount rate used by other major mobile gaming companies such as Activision Blizzard, Inc. (5Y DCF Growth Exit for Activision Blizzard, n.d.). As we were not provided any acquisition costs, we assume acquisition costs to be zero.

Summary information for computed CLV for each group (0 - did not join, 1 - joined) as follows:

Data2CLV$`Joined?` <dbl>	CLVP1 <dbl>	CLVP2 <dbl>	TotalCLV <dbl>
0	3948.667	1509.151	5457.818
1	4046.000	1546.351	5592.351

At a glance, we observe an increase in both periods for CLV . We conduct a t-test to determine whether the difference in average CLV is significant.

<u>T-Test</u>

Hypothesis:

- H_0: $\mu_0 = \mu_1$ (no difference in average CLV)
- H_1: $\mu_0 < \mu_1$ (average CLV of population 0 is less than average CLV of population 1)

```
        Welch Two Sample t-test

data:  Gamers_NoComm2$TotalCLV and Gamers_Comm2$TotalCLV
t = -8.296, df = 177.82, p-value = 1.298e-14
alternative hypothesis: true difference in means is less than 0
95 percent confidence interval:
    -Inf -17.256
sample estimates:
mean of x mean of y
 46.64802  68.19941
```

The p-value obtained is significant, leading us to reject the null hypothesis and conclude that the average CLV of the control group was less than that of the test group.

Linear Regression

We also build a linear regression for the total CLV and the online community variable to determine the relationship and obtain the magnitude of difference in CLV among players.

$$y = ß_0 + ß_1 x_1$$

Where:

y = CLV

x_1 = joining the online community

Our results from the linear regression are as follows:

```
Call:
lm(formula = CLV ~ Joined2, data = Data2CLV)

Residuals:
    Min      1Q  Median      3Q     Max
-34.566 -14.858   0.449  16.293  30.294

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)   46.648      1.677   27.82  < 2e-16 ***
Joined2       21.551      2.612    8.25 2.22e-14 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 18.14 on 197 degrees of freedom
Multiple R-squared:  0.2568,    Adjusted R-squared:  0.253
F-statistic: 68.07 on 1 and 197 DF,  p-value: 2.224e-14
```

The linear regression model: $y = 46.648 + 21.551x_1$

The overall model is statistically significant based on the global F-test. The intercept is 46.648 and is highly statistically significant, indicating that in the absence of the online community feature, the average CLV (per customer) was $46.65. This model also provides us with an idea of the magnitude of change in CLV provided by the online community, where for a particular user, an additional $21.55 to their CLV can be observed if they join.

We have seen that the online community feature appears to have an effect on user revenue, retention rates, and CLV. We note again that this appears to be short-term.

Appendix E: Campaign/Organic: Additional Variable Exploration

In Data 3, we are provided with information on a new variable, Campaign/Organic, which tells us whether the customer joined the game through a campaigning effort of the firm or through organic means. This may be an indicator of the following:

3. Effectivity of paid versus “organic” marketing strategies of the firm (Grguric, 2021)
4. A player’s authentic interest in the game which may affect likelihood of staying

This variable can be useful as an additional explanatory variable in building the regression model to explain user churn.

$$y = ß_0 + ß_1x_1 - ß_2x_2 - ß_3x_3 + ß_4x_4$$

Where:

y = churn

x_1 = joining the online community

x_2 = customer age with the firm after launch of online community

x_3 = average spend in the last/latest three months of life with the firm

x_4 = campaign/organic

```
Call:
glm(formula = Churn ~ CampOrganic + OnlineComm + FirmAge + AveSpend,
    family = binomial(link = "logit"))

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.6987  -1.1934   0.7953   1.0871   1.3342

Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept)  0.355687   0.565412   0.629  0.52930
CampOrganic  0.179729   0.304496   0.590  0.55502
OnlineComm   0.930000   0.356426   2.609  0.00907 **
FirmAge     -0.052077   0.073166  -0.712  0.47661
AveSpend    -0.003006   0.005669  -0.530  0.59588
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 268.95  on 198  degrees of freedom
Residual deviance: 260.19  on 194  degrees of freedom
AIC: 270.19

Number of Fisher Scoring iterations: 4

(Intercept) CampOrganic  OnlineComm     FirmAge    AveSpend
  1.4271603   1.1968931   2.5345081   0.9492559   0.9969981
```

The logistic regression model: $y = 0.356 + 0.930x_1 - 0.052x_2 - 0.003x_3 + 0.180x_4$

Again, we can infer that firm age and average spend are insignificant. We also see that there is no significant relationship between whether the user joined organically or through a campaign and whether they churned. The AIC of this model is 270.19, higher than the initial churn model AIC of 268.54, which suggests that the inclusion of this variable may not be worthwhile in predicting user churn.