The Impact of Online Community Launch on Customer Value at KyngaCell

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EXECUTIVE SUMMARY

The report is a customer analysis on the mobile gaming company KyngaCell. We aim to quantify the impact of the online community introduction. Specifically, our team analyzed the information of 199 users about the short-term user expenditure change and long-term effects on user retention/churn and customer lifetime value (CLV). Meanwhile, we differentiated the user source through which users joined the game for further analysis.

Based on our analysis, the community launch has increased the individual user revenue for the first month. Overall, KyngaCell's total revenue rose by 11% and the margin per user increased by $29.07 in the first month after the online community launch. However, the margin increase did not compensate for the trenchant decline of the retention rate that CLV ended up waning by up to 20.6%. Then we segmented users based on channels through which users joined the game. The analysis indicates that users joined the game without campaign influence (organic users) had lower churn rate compared to those from campaign. These findings are limited to several assumptions, including independent users and short-term consistent margin increase.

According to these findings, we have several recommendations for KyngaCell Company. First of all, it is urgent to retain user engagement in the community for the overall churn increase from the community launch. For short-term user value, the company can attract more organic users to join the community for foreseeable monthly $29 increase by each user. On the other hand, in order to encourage user retention and increase CLV in the long run, we need more in-depth customer analysis, such as using customer segmentation to differentiate customer services.

INTRODUCTION

Mobile gaming industry has traditionally driven its revenue from its users [1] and mobile gaming powerhouse KyngaCell was trying to increase its revenue by launching an online community in the game. With this new feature, the company expected an upward change in the revenue and retention rate, and ultimately a positive impact on the CLV. However, without quantifying the impact, KyngaCell could not confirm the real effect of the launch. Therefore, the Chief Financial Officer delegated an analysis on 199 users that provide information on revenue, retention, CLV and their respective changes attributable to the introduction of online community.

DATA CHARACTERISTICS

The dataset has three subsets with information of 199 individual users (Plot 0). The first subset shows 41% of customer joined the online community, with the average one-month user spend increasing from $78 to $121 after the community launch. The second one reveals more than half of the users are new customers, joining the game in 3 months. Also shown in the second dataset is that the churn rate is up to 59% after the community launch. The third one combined the previous two datasets and added one variable of the user source, showing 62% of the users are from campaign, marketing or promotions.

MODEL SELECTION, EVALUATION, AND INTERPRETATIONS

The data provided allowed us to use a causal technique called Difference-in-Difference (DID) to quantify the extent of the impact on revenue. For the categorical variable, churn rate, we used a logistic regression model with a counterfactual approach. We also ran the same models after adding the new variable: 'Campaign/Organic' for further analysis. For the CLV calculation, we used the formula$CLV = \sum_{t=0}^{t} \frac{m \times r^t}{(1+i)^t}$ - AC and computed on an individual level. As the customer lifetime (t) is low (based on the relatively high churn rate), we used a 0 discount rate. Additionally, the acquisition cost (AC) was not provided and wouldn't impact on our analysis of the CLV change, so we suppressed the discussion on AC and focused on the margin (m) and retention rate (r).

Has the introduction of the community changed user revenue?

Before the community, the distributions of revenues of those who joined and who didn't were well balanced (Plot 1). After that, those who joined showed higher revenues. Statistically, it is possible to conclude that the online community had improved user revenue (Table 1). In addition, short-run impact on average revenue was approximately $29 per user in the first month after joining the community. We assume that this effect is permanent and projects into the future. As a consequence, the impact on quarterly user revenue was $87 more for joiners. And because of that we estimated that KyngaCell total revenue for the first month has been by 11% bigger.

Has the introduction of the community affected the churn?

Our analysis shows that users who joined community averagely are 2.5 times more likely to churn (Table2). The churn rate out of the 199 users is predicted to have increased from 54.5% to 78% because of the community introduction. In addition, the group size of users very likely to churn increased (Plots 2 and 3). This outcome was not expected since the company will end up losing customers in a faster pace. Nevertheless, as long as gains in revenues outperform KyngaCell may still benefit.

Has the online community led to an increase in customer lifetime value?

The introduction of the online community has caused the CLV to decline as we can see a clear drop in all quartiles of CLV in Plot 4, 5, and 6. The plots correspond to the computed data. When customer lifetime equals 2 quarters, the mean CLV falls by 21.8% as KyngaCell introduced the online community, and when the customer lifetime equals 3 quarters, the decrease is 25.9%, and 4 quarters is 28.4% (Table 3).

Has the user from different channels acted differently after introducing the online community?

We segmented users into two cohorts - Campaign/Organic. For users acquired through the campaign, joining the community still increases the churn rate. However, for organic users, joining the community has no significant impact on the churn rate. In other words, the probability of organic user leaving the game won't increase when they join the community. This is a valuable finding as each organic user will then contribute $29 more every month.

Limitations

First, we rely on several hypotheses, including that non-joiners expenditures are not indirectly affected by the introduction of a new community; trend before treatment are similar between joiners and non-joiners and that there are no unobservable factors affecting dependent variables. If these assumptions do not apply, our results may be completely biased. Also, despite the robustness of impact estimation, churn probability model has showed limited power in explaining the current churn rate, and may face limitations in explaining the overall churn level.

RECOMMENDATION

1. Adopting marketing strategies that attract organic users to join the community

The community created a more dispersed distribution of churn rates, and we have seen a difference after separating the organic users from those from campaign. Appropriate marketing strategies should be focused on organic users whose churn rate does not increase while joining the online community. In this way, the company can have a stable customer lifetime and increase the margin which leads to a higher CLV. Some examples of appropriate marketing strategies include the promotion and targeted advertising,

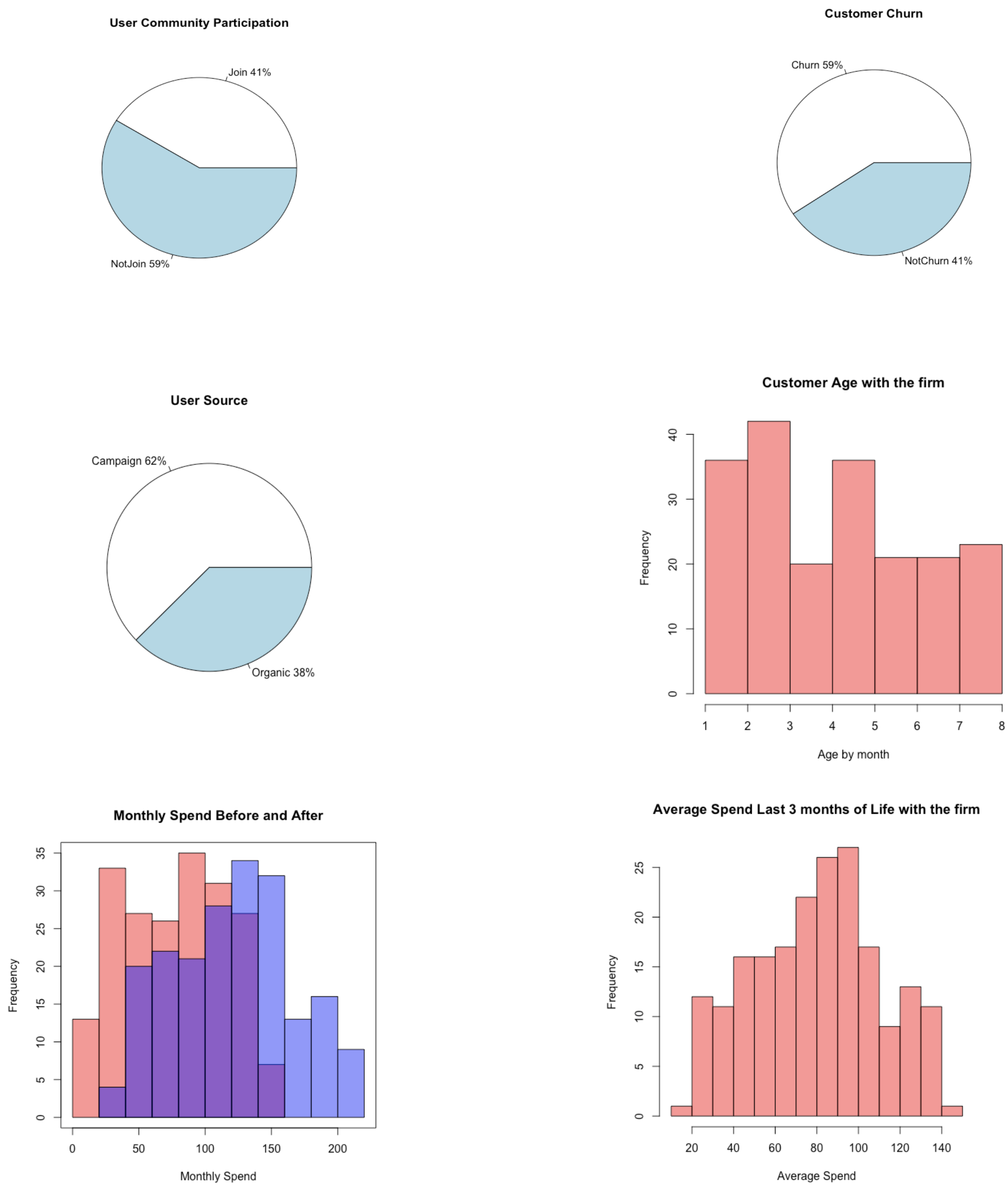
2. Control the churn rate of campaign users by conducting in-depth customer analysis

In our analysis, the online community features increased the churn rate for users under the influence of campaigning. Although an online community introduces a host of extremely powerful things like economic exchange and group identity, community members often migrate games as a whole. [2] Therefore, we recommend to conduct user behavior analysis to better serve customers joined from the campaign channel and provide better community management such as using the technique of iterating the community feature.

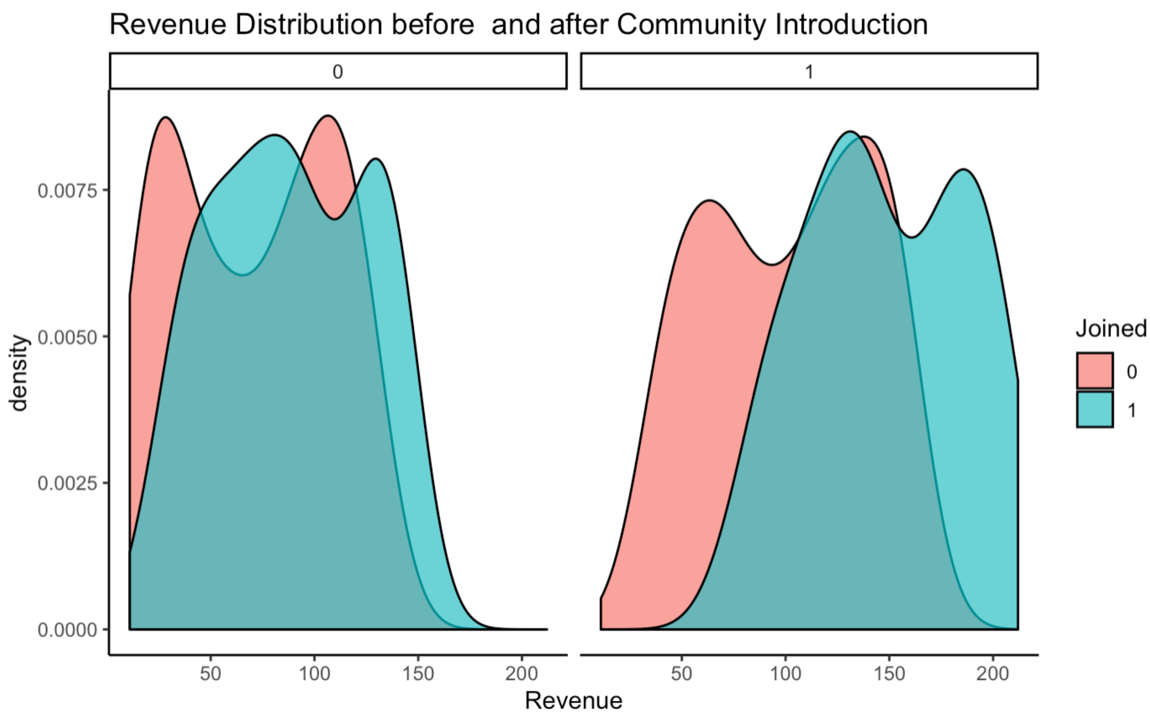
CONCLUSION

Users are spending more in the game after the introduction of the online community, but are more likely to churn in the meantime. Looking more closely into user components, those who joined the game organically are excluded from this impact. These findings call for further strategies on how to appeal to organic users to join the community and create active engagement with campaign users.

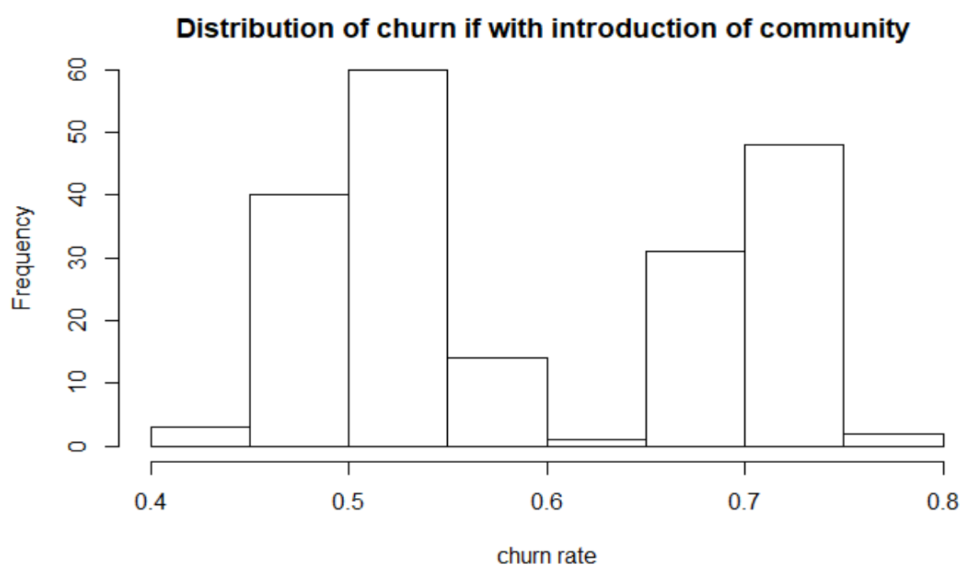
APPENDIX



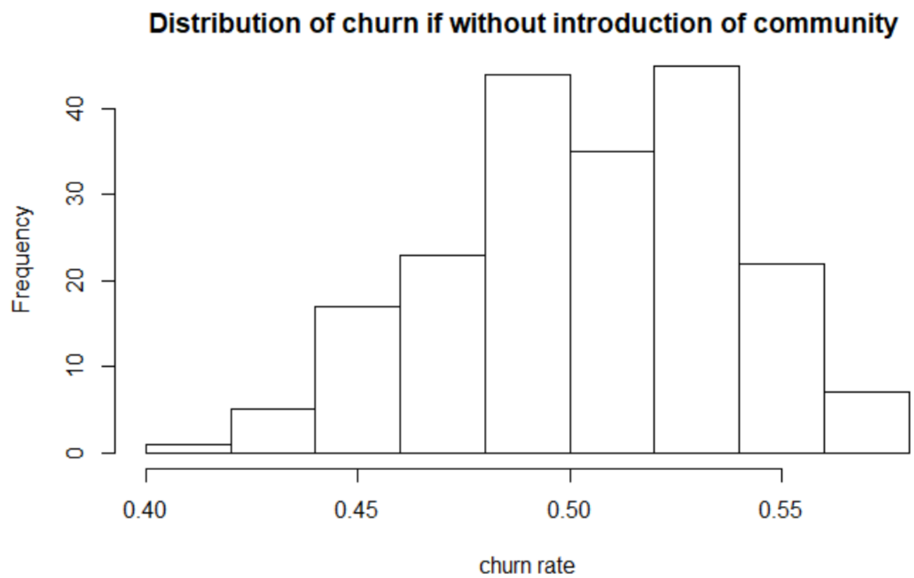
Plot 0


Revenue Distribution before and after Community Introduction
0
1
0.0075
0.0050
0.0025
0.0000
density
50
100
150
200
Revenue
Joined
0
1

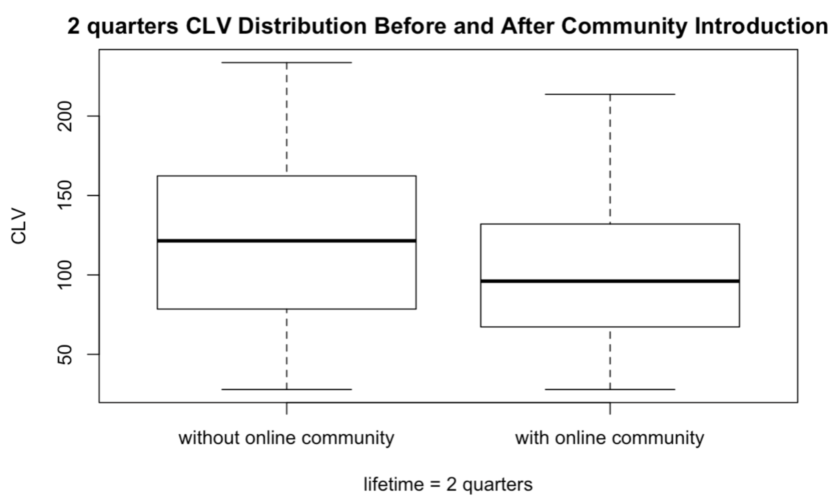
Plot 1


Distribution of churn if with introduction of community
Frequency
0
10
20
30
40
50
60
0.4
0.5
0.6
0.7
0.8
churn rate

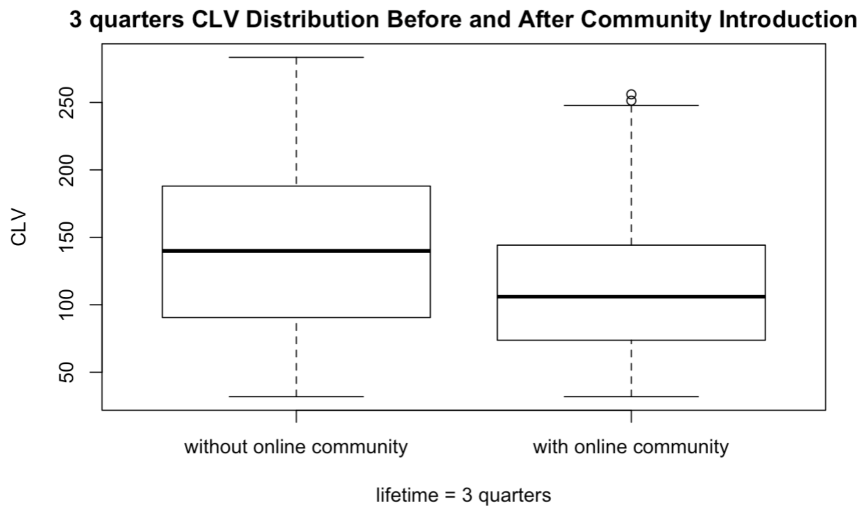
Plot 2


Distribution of churn if without introduction of community
Frequency
0
10
20
30
40
0.40
0.45
0.50
0.55
churn rate

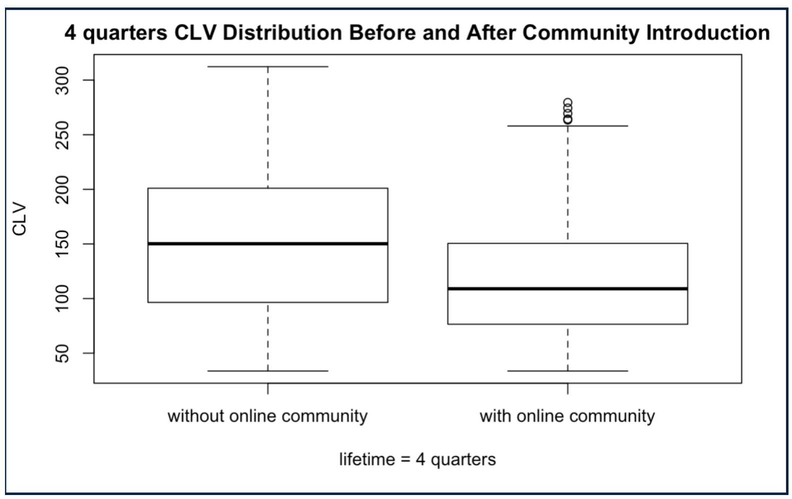
Plot 3


2 quarters CLV Distribution Before and After Community Introduction
CLV
50
100
150
200
without online community
with online community
lifetime = 2 quarters

Plot 4


3 quarters CLV Distribution Before and After Community Introduction
CLV
50
100
150
200
250
without online community
with online community
lifetime = 3 quarters

Plot 5


4 quarters CLV Distribution Before and After Community Introduction
CLV
50
100
150
200
250
300
without online community
with online community
lifetime = 4 quarters

Plot 6

Table1 - Revenue Model

```
Call:
lm(formula = Revenue ~ Joined + After + Joined * After, data = data1b)

Residuals:
    Min      1Q  Median      3Q     Max 
-75.024 -34.024   0.921  35.624  65.752 

Coefficients:
               Estimate Std. Error t value Pr(>|t|)    
(Intercept)      70.376      3.567  19.729  < 2e-16 ***
Joined1          17.758      5.557   3.196 0.001508 ** 
After1           30.872      5.045   6.120 2.27e-09 ***
Joined1:After1   29.018      7.859   3.692 0.000253 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 38.59 on 394 degrees of freedom
Multiple R-squared:  0.3408,	Adjusted R-squared:  0.3357 
F-statistic: 67.89 on 3 and 394 DF,  p-value: < 2.2e-16
```

Table 2 - Churn Model

```
Call:
glm(formula = Churned ~ Joined + Average_Spend + Customer_Age, 
    family = binomial(link = "logit"), data = churn)

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   
Joined1        0.917627   0.355216   2.583  0.00979 **
Average_Spend -0.002899   0.005657  -0.512  0.60836   
Customer_Age  -0.051796   0.073144  -0.708  0.47886   
---
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
```

Table 3

Summary of CLV as Customer Lifetime Equals 2, 3, 4 in Counterfactual and real-life setting

	2 quarter counterfactual	2 quarter	% change	3 quarter counterfactual	3 quarter	% change	4 quarter counterfactual	4 quarter	% change
min	27.891	27.891	0.000	31.875	31.875	0.000	33.692	33.692	0.000
1st quartile	78.513	67.269	-0.167	90.572	73.728	-0.228	96.502	76.523	-0.261
median	121.466	96.073	-0.264	139.978	106.013	-0.320	150.214	109.013	-0.378
mean	123.228	101.188	-0.218	144.196	114.492	-0.259	154.872	120.653	-0.284
3rd quartile	162.319	132.050	-0.229	187.997	144.218	-0.304	201.037	150.539	-0.335
max	233.642	213.659	-0.094	283.402	255.997	-0.107	312.268	279.499	-0.117

REFERENCES

1. Dmasper. (2017, December 6). Mobile Gaming is a $50b Industry. But Only 5% of Players are Spending Money (Part 1). Retrieved from https://medium.com/shopify-gaming/mobile-gaming-is-a-50b-industry-but-only-5-of-players-are-spending-money-f7f3375dd959

2. Koster, R., Williams, T., Williams, T., R, D., R, D., & BJWyler. (2019, January 31). What drives retention. Retrieved from https://www.raphkoster.com/2019/01/30/what-drives-retention/.