

Rewards Model AB Test

Executive Analysis

Final Business Recommendation & Executive Summary

Overview & Context

Our product team launched an AB Test on Oct 7th, testing a new Rewarded Ad Model.

This test has been running for 14-days and we have 13-days of complete data to analyse

Test-Setup

Within our games we show 2 types of Ads:

- Rewarded: User chooses to watch ad in exchange for in-game rewards
- 2. **Interstitial:** Ad appears automatically after every 2 losses

This test has 2 variations:

- Control Group: Default ads model
- 2. **Test:** We're offering more in-game rewards, to see if we can incentivise more users to watch a reward ad

Test-Goal

- 1. *Increase product engagement* (retention rate & ad impression views)
- 2. Thereby *increasing the average revenue per user* (ARPU)

Key Takeaways

КРІ	Control Group	Test Group	Δ
Total Users	42,571	42,707	-
Users: D7	24,914	25,140	-
Retention Rate [%]: D7	4.50%	4.40%	-2.20%
ARPU [\$]: D7	\$0.30	\$0.29	-3.30%
Ad Impressions per User: D7	3.69	3.64	-1.40%

Key Findings

- 1. There is **no evidence** that the tested rewards has a positive impact on product engagement or revenue
- 2. We observe a decrease all KPIs, after 7-days
- 3. We retain fewer users (-2.2%), they few fewer ads (-1.4%) which translates into lower revenue per user (-3.3%)

Important to Note

- 1. The results are not yet statistically significant as of yet
- 2. For each user added to the experiment, we need to wait 7-days until we have complete data for user
- 3. Approx. 60% of the users in the experiment meet that criteria. For the remaining 40% we need to wait 7-days.

Strategic Next Steps

As of today, we **should not roll-out the experiment** X The test group shows a decrease across all KPIs.

We have 3 Options:

- Roll-out the test
- Scale the test
- Abandon Test / Pause the test

Considerations

- 1. What other AB Tests do we have ready to launch?
- Is there a risk of keeping the test running?

Recommendation

- 1. Pause the test. Don't add any new users to the experiment.
- 2. Keep the users in the 'test_group' variation, for now.
- 3. Re-analyse the test next week, once the entire cohort of users has been in the experiment for at least 7-days
- 4. Align with Product. What does our testing pipeline look like? Do we have better tests in backlog?
- 5. **Yes** > Consider Abandoning this Test. **No** > Refine this test and resume.

Executive-Level Data Visualization

AB Test Summary: KPI Tables

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Observations

- Decrease across all engagement and monetization KPIs
- Approx. 60% of users have been in the test for at least 7-days
- We see the key business drivers of gaming at play. Revenue is a function of retaining and engaging users (ad impressions)
- When both engagement (-1.4%) and retention (-2.2%) drops, it has a multiplying effect on revenue (-3.3%)

Revenue per User: D7

ARPU [\$]: D7

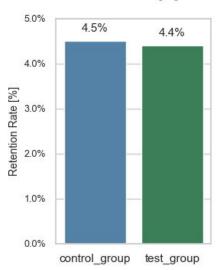


Insights

- We observe a -3.3% decrease for the test group vs the control group
- The decrease is not statistically significant

■ Retention Rate D7

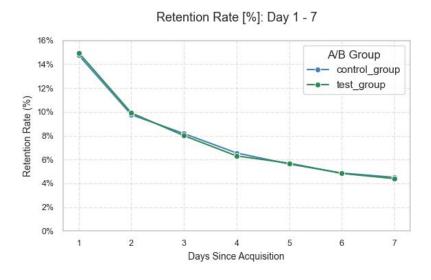
Retention Rate [%]: D7



Key Takeaways:

- We observe a -2.2% decrease for the test group vs the control group
- The decrease is not statistically significant
- Retention is the cornerstone of LTV / ARPU; even small % drops at scale result in material revenue loss.
- Focus area: **improving early user experience** for better engagement.

Retention Rate Curves: D1 -7

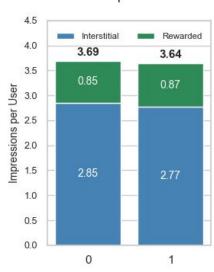


Key Takeaways:

- The dynamics of the retention rates essentially identical
- Within gaming, retention rate curves mirror exponential decaying

Ad Impressions per User

Ad Impressions



Observations:

- Test group shows a **slight drop in interstitial ad impressions**.
- Rewarded impressions are flat indicating users aren't necessarily choosing to watch more rewarded ads.

* Al Optimization

- Ad Frequency Optimization: Predict optimal timing to balance revenue vs retention
- Churn / Retention Prediction Models: Flag users likely to drop out early
- LTV Prediction Models: Make early LTV estimations (e.g. after 3 days)
- Personalized Experiences: Use AI to customize onboarding / tutorial flow for retention gains