Optimizing Push Notification Permission Timing
A/B Test, Retention & Predictive Modeling

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Experiment Setup

Goal

Evaluate the optimal timing for the push notification permission popup.

Design

- Random A/B split based on login_id parity
- **Group 1 (even):** popup shown immediately after installation
- **Group 2 (odd):** popup shown after completing the tutorial (5 battles)

Key Metrics

- **Opt-in (Hit rate):** share of players allowing notifications
- **Retention:** Day 1, Day 7, Day 14

Data Overview

Participants

Approximately **5,000 users** included in the experiment window.

Data Sources

- `notification_allowed.csv`: one record per exposed user (allow/deny + exposure day)
- `user_history.csv`: daily behavioral telemetry per active user

Feature Categories

- **Engagement:** playtime, sessions, battles played
- **Progression:** ELO rating, arena level, upgrades
- **Economy:** gold gained, cards/runes activity

Experiment Validity Checks

Group Split Balance (SRM)

- Group 1: 2,489 users | Group 2: 2,490 users
- Chi-square SRM test: $\mathbf{p = 0.989} \Rightarrow$ no allocation issue

Exposure Differs by Design

Group	Total users	Exposed users	Exposure rate
group1_even	2489	2487	99.9%
group2_odd	2490	1372	55.1%

Primary Result: Hit Rate (Intent-to-Treat)

Metric Definition

Hit rate computed over **all assigned users** (ITT)

Group	Users	Allowed	Hit rate	95% CI
Group 1 (early)	2489	1434	57.6%	[55.7%, 59.6%]
Group 2 (late)	2490	861	34.6%	[32.7%, 36.4%]

Statistical Conclusion

- Difference: **+23.0 pp** (group1 – group2)
- Two-proportion z-test: $\mathbf{p} \approx 9 \times 10^{-60} \Rightarrow$ highly significant

Exposed-only View: Conditional Performance

Group 1 — Popup Immediately

57.7%

Opt-in rate among exposed users

Group 2 — Popup After Tutorial

62.8%

Opt-in rate among exposed users

Delayed popup converts slightly better when reached, but many users never reach it due to tutorial drop-off.

Retention Impact Summary

Group	Day 1	Day 7	Day 14
Group 1 (early)	42.5%	23.9%	18.0%
Group 2 (late)	45.9%	25.1%	18.6%

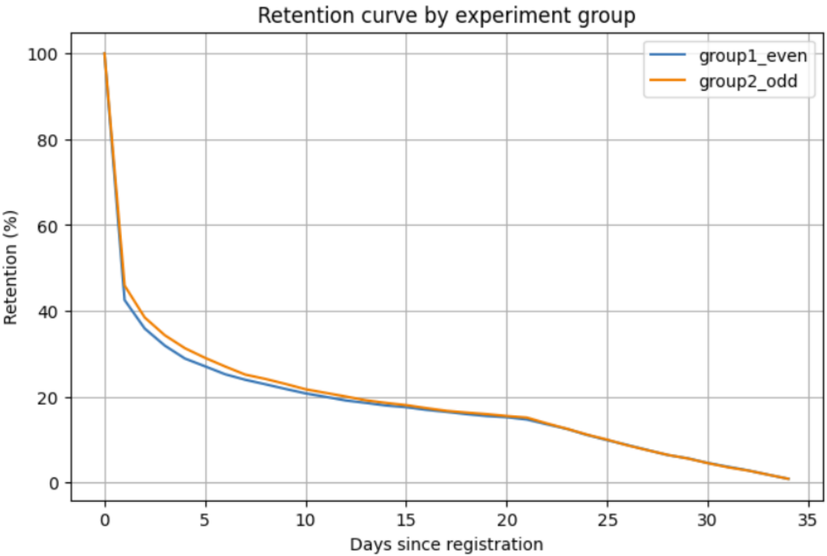
Statistical Significance (Two-proportion z-test)

- **Day 1:** $\Delta = -3.4$ pp, $\mathbf{p = 0.017}$ $\Rightarrow$ significant
- **Day 7:** $\Delta = -1.2$ pp, $p = 0.33 \Rightarrow$ not significant
- **Day 14:** $\Delta = -0.6$ pp, $p = 0.59 \Rightarrow$ not significant

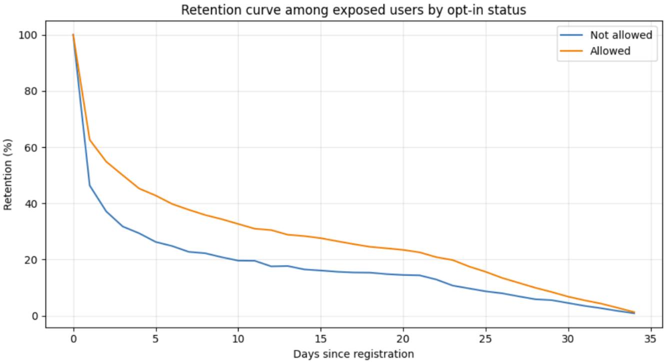
Business Interpretation

Early popup slightly reduces Day 1 retention but shows **no statistically significant impact** on medium or long-term retention.

Retention Curves by Experimental Group



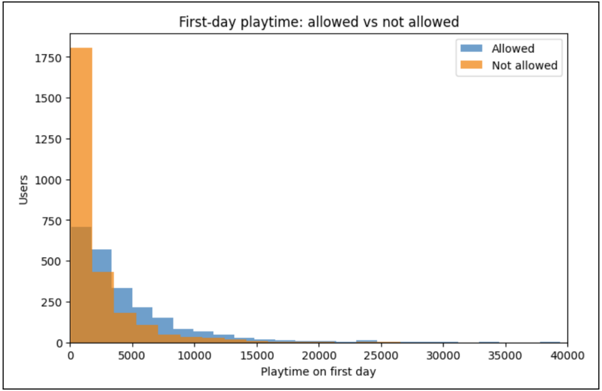
EDA: Retention by Opt-in Among Exposed Users (Descriptive)



Key Observations

- Even among exposed users, opt-in players retain substantially better over time
- The gap emerges early (already after Day 1) and persists across the horizon

EDA: Early Engagement vs Notification Opt-in



Median playtime — **Allowed: 2,915** | **Not allowed: 1,130**

Difference is statistically significant (t-test, **p** $<$ **0.001**)

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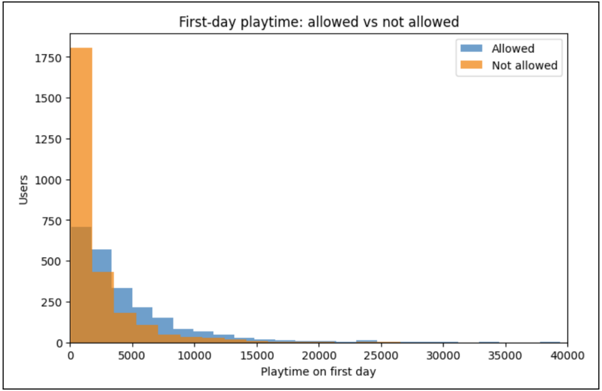

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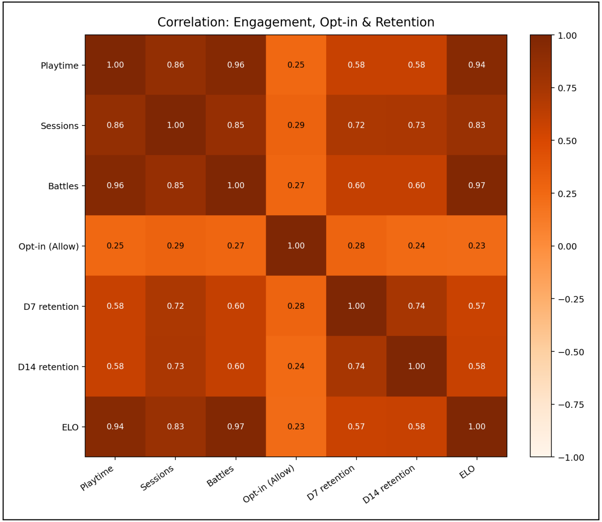
Correlations: Engagement Drives Opt-in and Retention



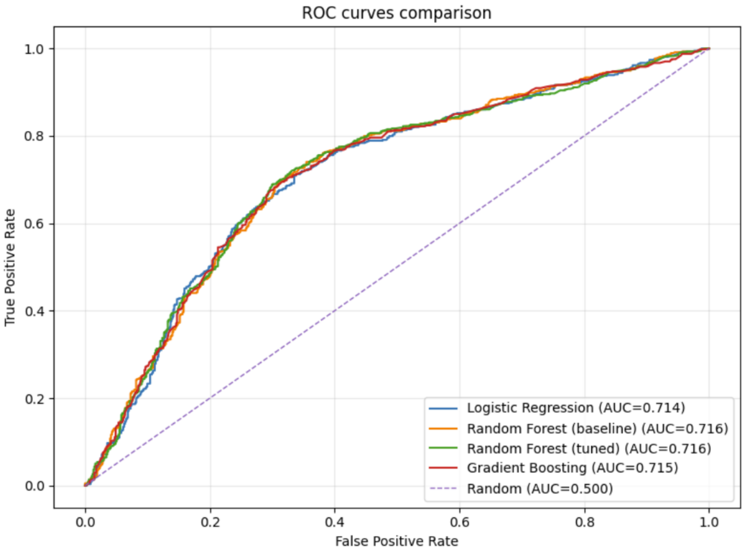
Segment Analysis: Effect Robustness

Early popup improves opt-in rate across all major segments

- **Acquisition channel**
  - Paid users: **+24.2 pp**
  - Organic users: **+21.9 pp**
- **Monetization**
  - Non-payers: **+23.2 pp**
  - Payers: **+8.2 pp** (small sample)
- **Geography (top markets)**
  - Uplift ranges from **+16 pp to +30 pp** across all countries

No segment shows a negative effect — the uplift is globally consistent.

Predictive Modeling: Opt-in Prediction (ROC curves comparison)



Predictive Modeling: Opt-in Prediction (Leakage-Safe)

Setup	Model(s)	AUC
Leakage present (telemetry after exposure)	RF	**0.76**
Leakage removed (early-only features)	LR / RF / GB	**0.71**

Key Takeaways

- Early engagement features already provide strong predictive signal
- More complex models do not outperform Logistic Regression
- **Leakage detected:** post-exposure features dominated feature importance

Predictive Modeling: Retention Is Highly Predictable

Target	Base rate	Model	AUC
D7 retention (`retained_d7`)	0.245	Logistic Regression	**0.97**
D14 retention (`retained_d14`)	0.183	Logistic Regression	**0.96**

Key Takeaways

- Retention can be predicted very accurately using first-day behavior + registration attributes
- Early engagement signals strongly determine medium-term and long-term retention
- **Sanity check:** shuffling labels gives AUC ≈ 0.50, confirming the signal is real

Executive Summary & Recommendations

What We Learned

- Early popup increases opt-in by **23 pp** (highly significant)
- Small Day 1 retention drop; **no significant** impact on Day 7/14
- Opt-in strongly linked to **early engagement behavior**
- Early engagement predicts opt-in well (**AUC $\approx$ 0.71**)

Recommended Actions

- **Roll out early popup globally** to maximize notification reach
- **Smooth Day 1 friction** via softer UX (copy, timing, light nudges)
- **Leverage ML targeting:**
  - High engagement $\rightarrow$ prompt early
  - Low engagement $\rightarrow$ delay and focus on onboarding