

# Part 1: Funnel and Experiment Analysis

## Analysis Objective

Determine at which onboarding stages the greatest user loss occurs and assess the proportion of users passing through each funnel stage. This will help identify key optimization points for the user journey and increase conversion to purchase.

## Data Description

The analysis used events from the Simple App web funnel for the period January–April 2024. The sample includes 100,000 unique users and 346,328 events.

Main event types:

- onboarding\_start — start of funnel progression
- profile\_start — start of profile filling
- email\_submit — email address input
- paywall\_show — payment screen display
- payment\_done — successful purchase

## Methodology

For each user, the maximum stage they reached was determined.

Then calculated:

- Absolute number of users at each stage
- Proportion of users from the initial number (conversion)
- Loss proportion between stages

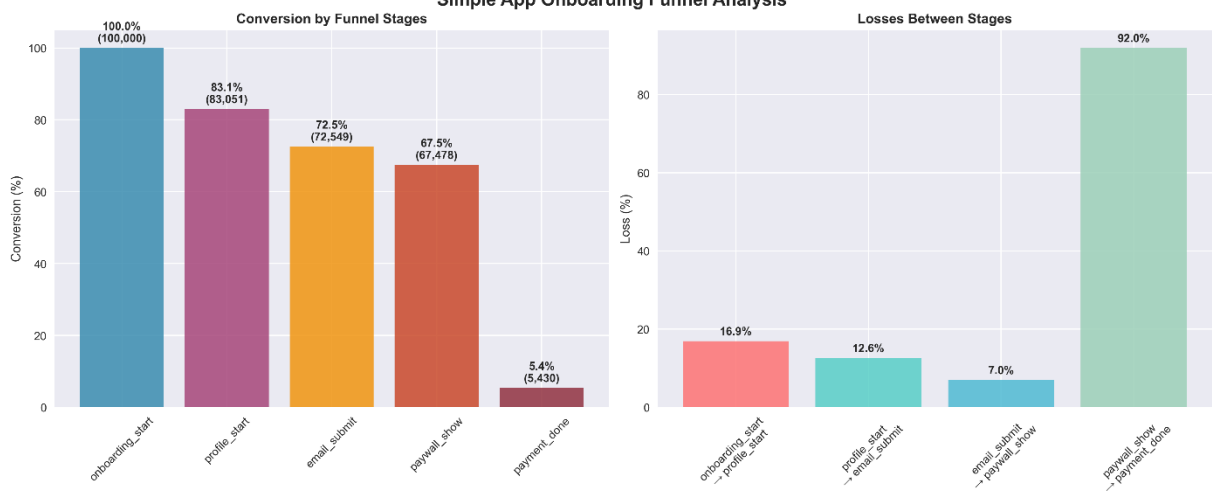
## Results

### Conversion by Funnel Stages

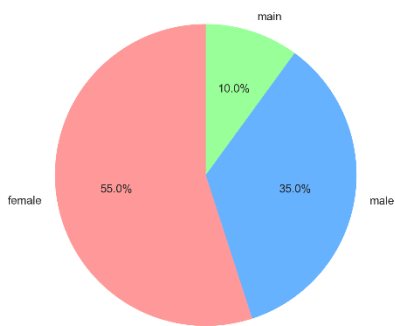
Stage	Users	Conversion from Start (%)	Losses between stages
onboarding_start	100,000	100.0	
profile_start	83,051	83.1	-16.9%
email_submit	72,549	72.5	-12.6%
paywall_show	67,478	67.5	-7.0%
payment_done	5,430	5.4	-92.0%

Visualization

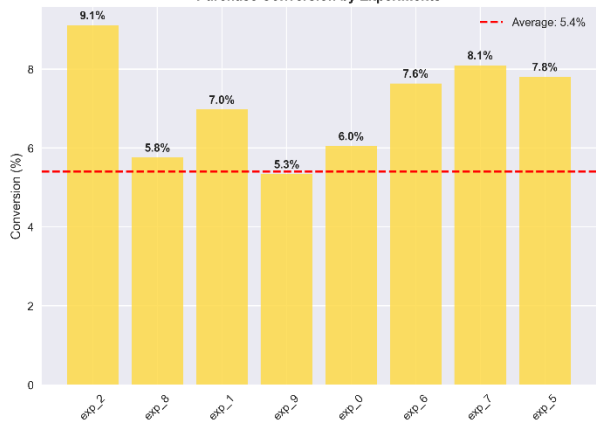
Simple App Onboarding Funnel Analysis



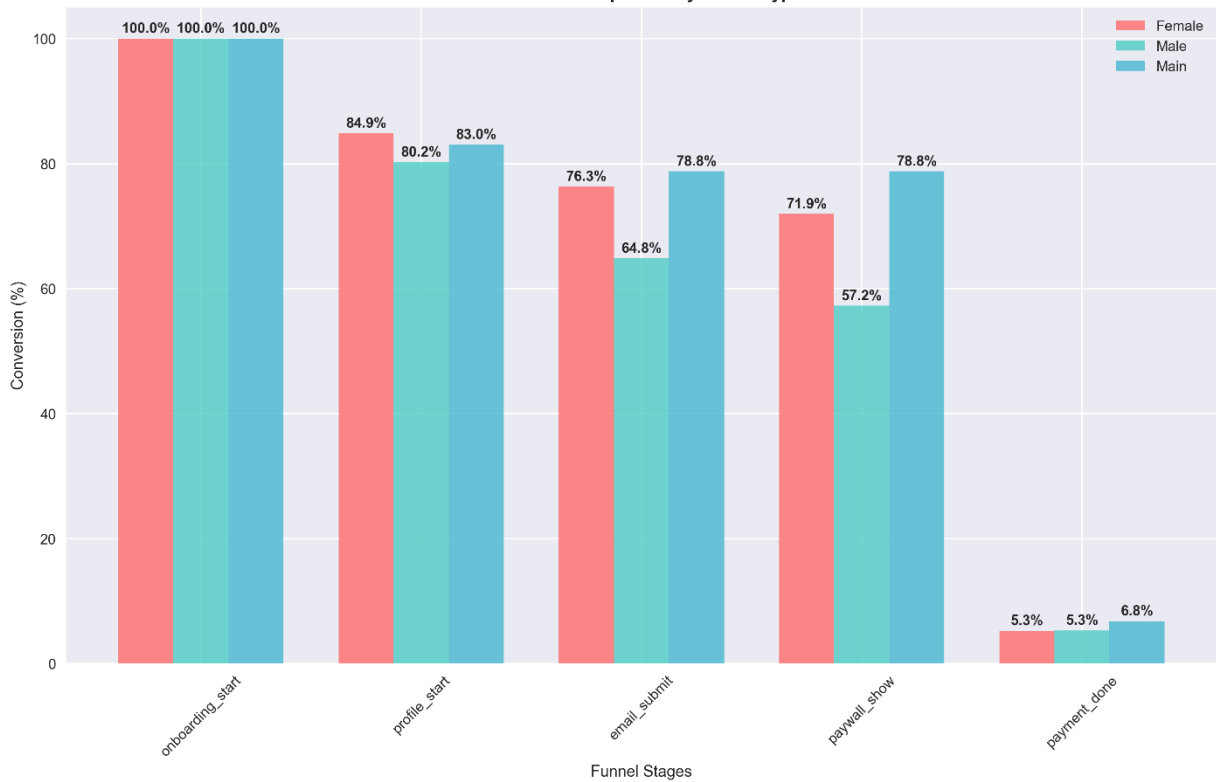
Distribution by Funnel Types

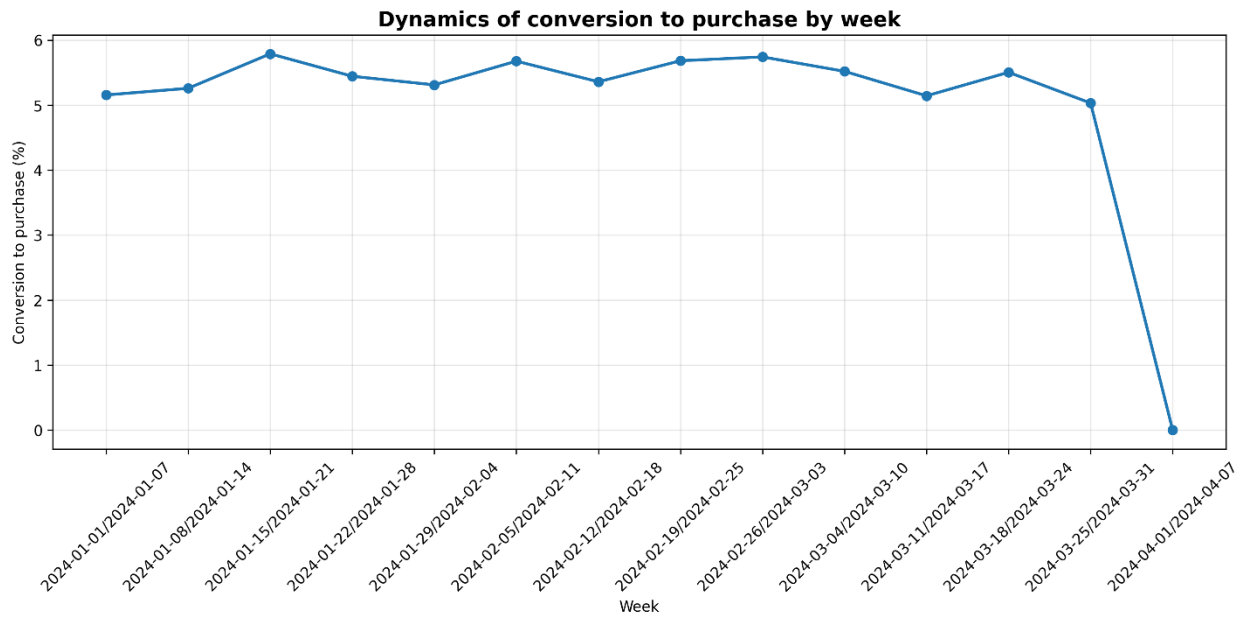


Purchase Conversion by Experiments



Conversion Comparison by Funnel Types





### Key Findings

- **Critical loss point — payment stage (paywall):** 92% of users who reach this step do not make a purchase.
- **Overall purchase conversion:** 5.4% of starting users.
- **Biggest funnel bottleneck:** the final stage requiring priority attention.

## Experiment Analysis (experiment\_exposure)

### Analysis Objective

Assess the impact of conducted A/B tests (experiment\_exposure) on purchase conversion, identify the most promising experiments, and justify the selection.

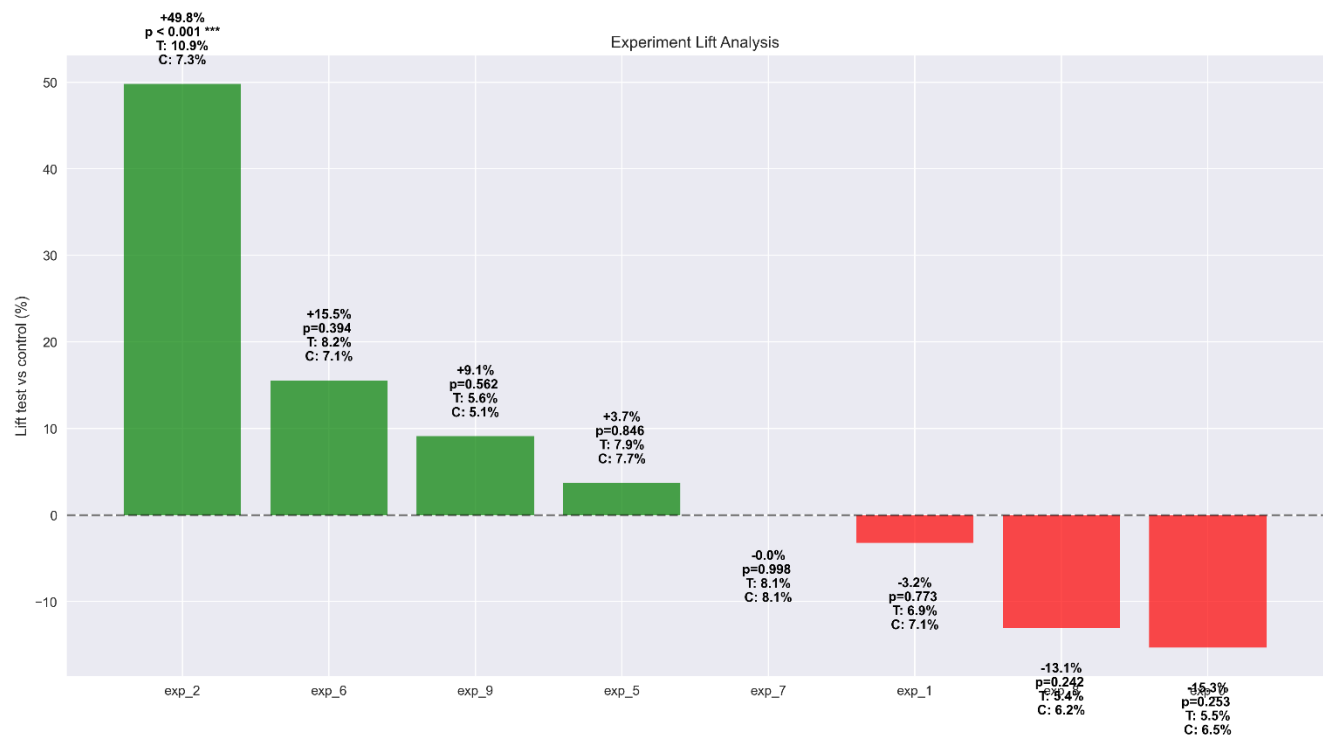
### Methodology

- For each experiment\_exposure event, determined:
  - Experiment name and group (control/test)
  - Number of unique users in each group
  - Purchase conversion (proportion of users who completed payment\_done)
  - Statistical significance of difference between groups (p-value)
  - Relative conversion increase (lift)

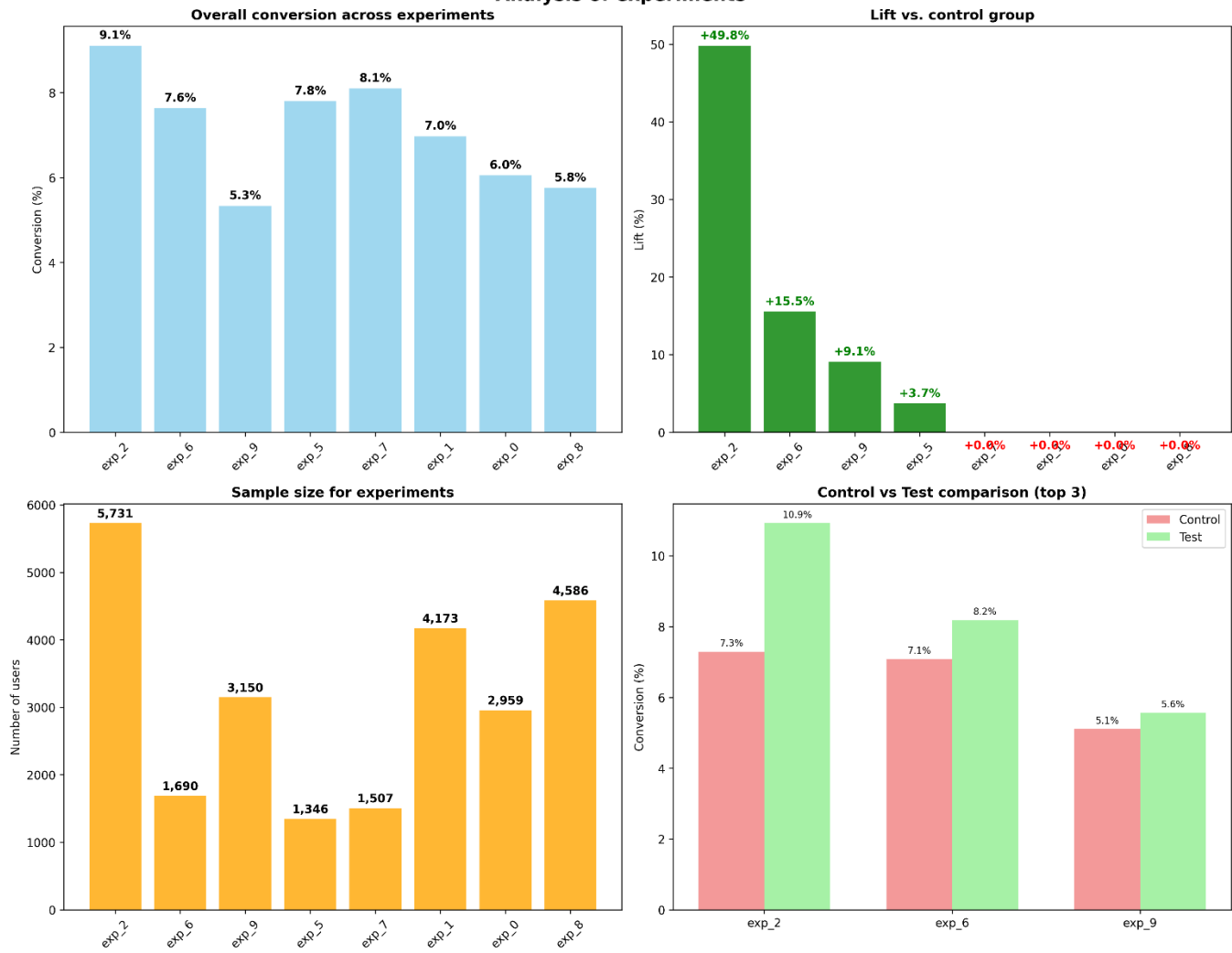
### Results:

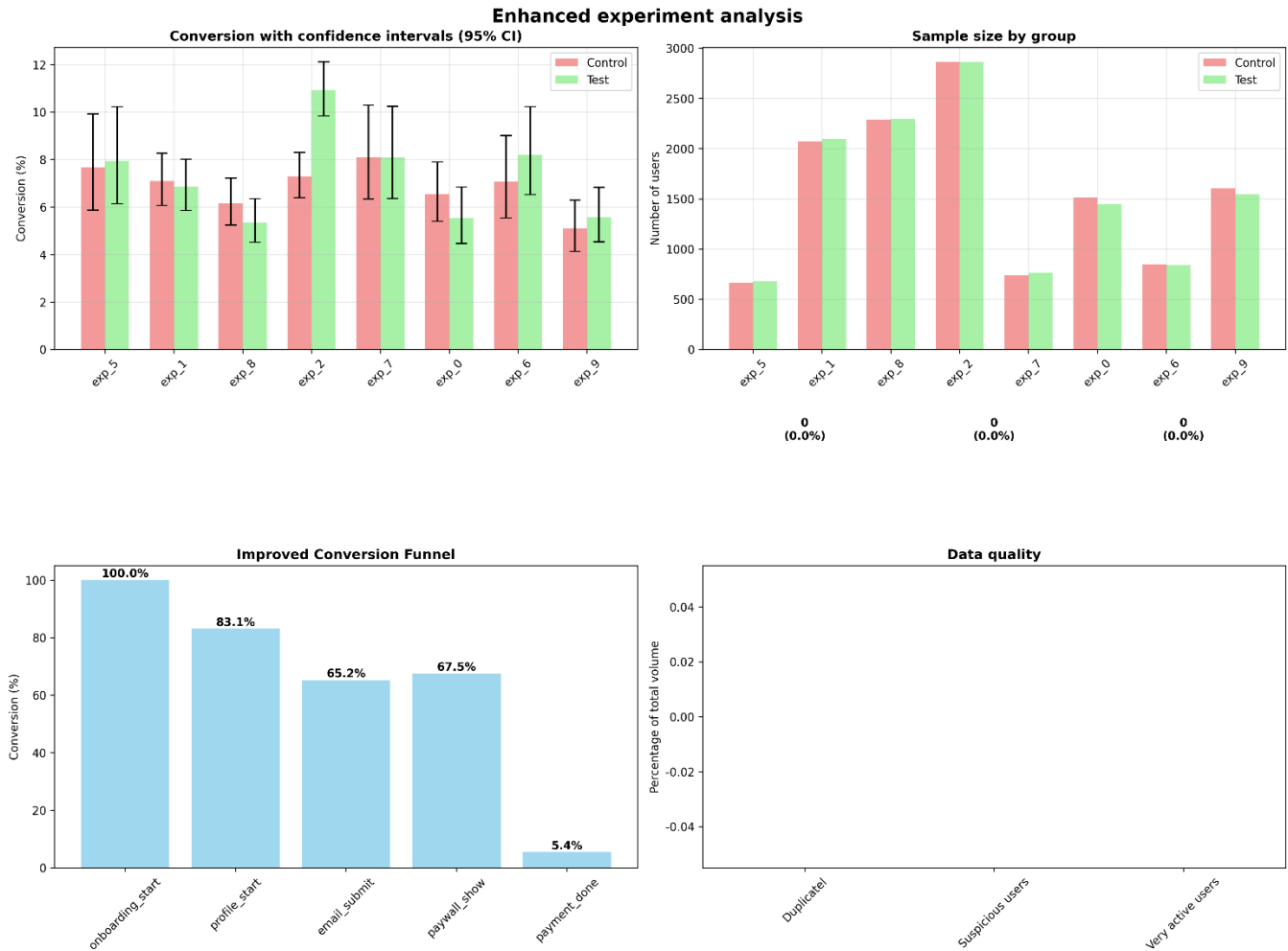
Experiment	Group	Users	Conversion (%)	Lift (%)	p-value	Conclusion
exp_2	control	2,866	7.3	—	—	
	test	2,865	10.9	+49.8	<0.001	<b>Recommended</b>
exp_6	control	847	7.1	—	—	
	test	843	8.2	+15.5	0.39	Requires refinement
exp_9	control	1,606	5.1	—	—	
	test	1,544	5.6	+9.1	0.56	Requires refinement

Visualization



Analysis of experiments





### Justification for Top-3 Experiment Selection

1. **exp\_2**
  - Most significant conversion increase: +49.8% (10.9% vs 7.3%)
  - Statistical significance:  $p < 0.001$
  - **Recommendation:** scale to entire audience
2. **exp\_6**
  - Positive lift: +15.5%
  - Statistical significance not reached ( $p = 0.39$ ), but effect is positive
  - **Recommendation:** refine hypothesis and repeat test
3. **exp\_9**
  - Positive lift: +9.1%
  - Statistical significance not reached ( $p = 0.56$ )
  - **Recommendation:** requires additional testing

**Experiments with negative effects are excluded from the table and not recommended for implementation.**

### Recommendations

- Conduct detailed analysis of the payment screen (UX/UI, value proposition, pricing).
- Consider testing new paywall scenarios (e.g., personalization, additional value explanations, alternative offers).

- Implement or test extended trial period (free trial) — give users the opportunity to try premium features without risk. This will demonstrate real product value and reduce payment concerns.
- Conduct separate testing of user behavior during extended trial period:
  - Track which features are used most frequently.
  - Emphasize most “selling” features in communication and interface.
- Use obtained data to form hypotheses for A/B testing.

#### **Examples of Metrics for Trial Period Behavior Analysis**

- **Feature Adoption Rate:** proportion of users who tried each key feature.
- **Conversion by Feature Usage:** conversion to payment among those who used a specific feature compared to others.
- **Frequency of Use:** average number of feature uses during trial period.

*These metrics will help identify the most “selling” features and emphasize them in communication and product.*

## **Part 2. Daily Tasks: Assessment, Improvements, Prospects**

### **2.1 How to Evaluate the Effectiveness of Daily Task Assignment**

I recommend using a comprehensive approach including quantitative and qualitative metrics:

#### **Key Metrics for Evaluation:**

- **Acceptance Rate** — proportion of users who accept suggested tasks.
- **Replacement Rate** — proportion of users who request task replacement.
- **Completion Rate** — proportion of completed tasks among accepted ones.
- **Retention Rate** — retention of users using daily tasks compared to control group.
- **Engagement Score** — average number of interactions with tasks (e.g., completion marks, comments).
- **Time to Completion** — average time to complete a task.
- **Feature Adoption** — proportion of users who used the daily tasks feature at least once.

#### **Behavior Analysis:**

- Tracking task usage patterns: which tasks are completed most often, at what time, with what frequency.
- Analysis of action sequences: what users do before and after completing tasks.
- Studying correlation between task completion and use of other product features.
- Analysis of time spent in product before and after implementing task system.

## 2.2 What Improvements and Changes Can Be Proposed (Based on Funnel Analysis)

Based on Part 1 results:

- Main problem — low conversion to purchase at paywall stage.
- Users leave without seeing real product value.

### Recommendations:

- Integrate daily tasks into free/trial period before paywall. Allows users to “feel” product benefits before payment.
- Demonstrate key “selling” features through tasks.
- Personalize tasks based on onboarding data and user behavior: which features they use most, what types of tasks they enjoy completing, when they are most active.
- Implement analytics on task usage during trial period. Identify which tasks are most often completed by those who later purchase subscription and emphasize them.
- Test different task formats (gamification, challenges, social elements). Increases engagement and retention.

## 2.3 How to Evaluate the Prospects of “Daily Tasks” Feature at Idea Stage

If the feature is only at idea level:

- Analysis of existing data:
  - Study current behavior patterns: is there a segment that already “sets tasks for themselves,” uses reminders, plans activities.
  - Competitor analysis: how it’s implemented elsewhere, what mechanics work, what problems they solve.
  - App Store/Google Play review analysis: what users request, what they complain about.
- Product behavior analysis:
  - Are there users who regularly return to the app?
  - Which features are used most often and with what frequency?
  - Is there correlation between usage frequency and retention?
- Build MVP/prototype:
  - Launch simple version on limited audience.
  - Measure key metrics: adoption, retention, engagement.
- Assess business potential:
  - How the feature can impact key metrics (retention, conversion, LTV).
  - Monetization scenarios (e.g., some tasks — only for paid users).