Mondly

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Task & Objective

Goal

Analyze Mondly user data to evaluate the impact of the Smart Recommendation feature and surface actionable insights for product and UX improvement.

Scope:

- Clean and preprocess user data
- Measure feature adoption and user impact (KPIs)
- Identify qualitative pain points and propose targeted recommendations

So what?

Understanding Smart Recommendation’s impact helps prioritize engineering and UX resources on features that drive adoption, satisfaction, and retention.

Executive summary

- **Adoption:** 97% of users tried Smart Recommendation at least once.
- **Impact:** Smart Rec users showed +14% higher usage and longer retention, but uplift was not statistically significant (likely due to small control group).
- **Key Pain Points:** Feedback clusters highlight repetitive/irrelevant recommendations, interface confusion, and slow performance.
- **Action:** Focus on Smart Rec personalization, onboarding for older/low-engagement users, and UI/performance fixes.
- **Opportunity:** The biggest gap in daily engagement is in the 30–59 segments—targeted product and UX improvements here could unlock the most significant growth.
- **Limitations:** Most user feedback is repeated, limiting qualitative depth; results are indicative, not conclusive.

Data Engineering

```
🧼 BASIC DATA QUALITY REPORT

📋 Schema Overview
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 10 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   user_id                  1000 non-null   int64
 1   age                      1000 non-null   int64
 2   gender                   1000 non-null   object
 3   location                 1000 non-null   object
 4   signup_date              1000 non-null   datetime64[ns]
 5   last_login               1000 non-null   datetime64[ns]
 6   smart_rec_usage_count    1000 non-null   int64
 7   total_usage_count        1000 non-null   int64
 8   user_satisfaction_rating 1000 non-null   int64
 9   user_feedback            1000 non-null   object
dtypes: datetime64[ns](2), int64(5), object(3)
memory usage: 78.3+ KB
None

🔍 Data Type Expectations
❌ user_id: int64 (expected: object)
✅ age: int64 (expected: int64)
✅ gender: object (expected: object)
✅ signup_date: datetime64[ns] (expected: datetime64[ns])
✅ last_login: datetime64[ns] (expected: datetime64[ns])
✅ total_usage_count: int64 (expected: int64)
✅ smart_rec_usage_count: int64 (expected: int64)
✅ user_feedback: object (expected: object)

📦 Mixed data types
✅ Columns with mixed types: 0
```

```
📦 Duplicate Checks
✅ Duplicated rows: 0
✅ Duplicate user_ids: 0

📈 Usage Logic Checks
✅ total_usage = 0 but smart_rec > 0: 0
✅ smart_rec_usage_count > total_usage_count: 0

📆 Date Integrity
✅ last_login before signup_date: 0
✅ Future last_login timestamps: 0

📊 Outlier Detection
✅ Age outliers (<10 or >100): 0
✅ Usage outliers (>1000): 0

🕳 Missing Value Summary
✅ No missing values detected

🎭 Uniformity Check
✅ All columns have variability

💬 Feedback Quality
✅ Empty feedback entries: 0
❌ Duplicated feedback entries: 990

📉 No Usage Detection
✅ Users with no usage: 0

🟠 No Smart Recommendation Usage
⚠️ Users with no smart recommendation usage: 31
```

Dataset:

- 1,000 users, demographics, feature usage, satisfaction, free-text feedback.

Cleaning Steps:

- Schema/null/duplicate checks, engineered: tenure, usage per day, churn flag, segments.

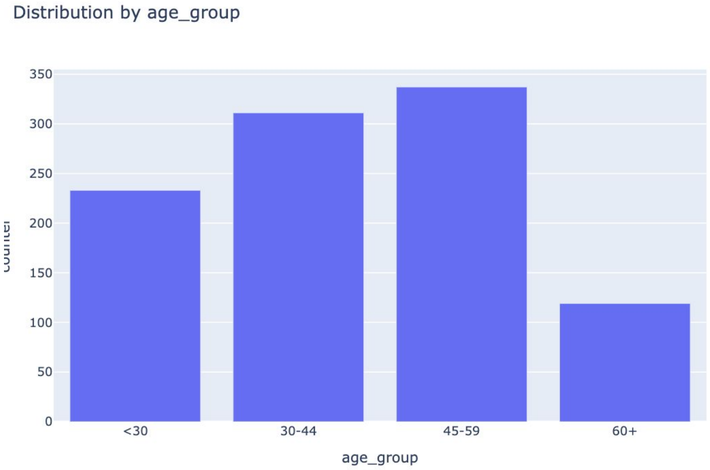
Limitation:

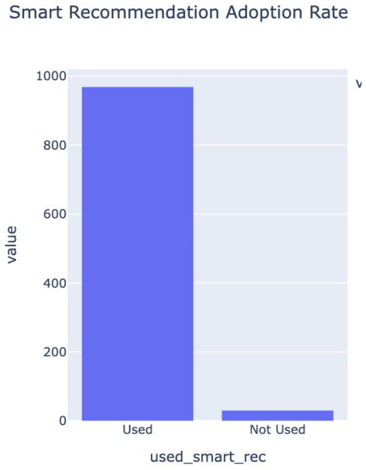
- 99% feedback text is duplicated—a synthetic data constraint for NLP.

Feature Engineering Summary

Feature Name	Description / Rationale
user_id	Cast as string to ensure consistent identification.
age_group	Age segmented into <30, 30-44, 45-59, 60+ for demographic analysis.
tenure	Days since signup—measures user lifespan/retention.
smart_rec_per_day	Smart Rec usage normalized by tenure—fair comparison across users.
total_usage_per_day	Total feature usage per day—controls for account age.
smart_rec_per_day_group	Bins users by frequency of Smart Rec usage per day (e.g., <0.1, 0.1-0.25, ...).
total_usage_per_day_group	Bins users by total usage per day (e.g., <0.1, 0.1-0.25, ...).
days_since_last_login	Recency metric to assess churn risk and retention.
recently_active	Flag for users active in last 30 days—segment for engagement.
likely_churned	Flag for users inactive >60 days—segment for churn analysis.
tenure_group	Bins users by total tenure: new (<30d), mid (30–90d, 90–180d), veteran (180+d).
used_smart_rec	Boolean: Did user ever use Smart Recommendation? (Key for adoption/impact KPIs)
usage_quartile	Users segmented into quartiles by total usage count (Q1=lowest, Q4=highest)—analyzes engagement spectrum.
smart_rec_share	% of user's activity that is Smart Rec—measures feature dependency.

Segment analysis

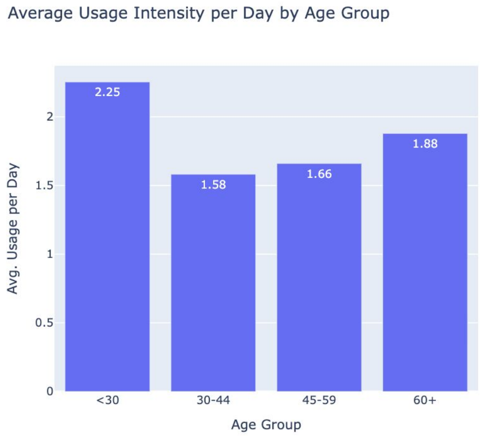


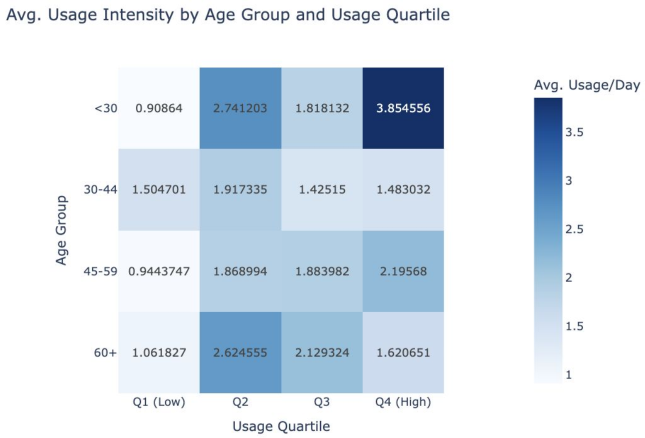


So what?

- Product and UX teams can focus efforts where the user base is largest and most active—primarily <30 and 60+ users—while not ignoring the specific needs of middle engaged segments.

Segment analysis





So what?

- While under-30s and 60+ users are highly active, daily usage dips among 30–59 year-olds.
- This usage gap is consistent across all engagement quartiles—suggesting a broad cohort trend, not just a few outliers.
- **Opportunity:** Tailored UX improvements and re-engagement in these middle-age segments could lift overall activity.

KPI Scorecard

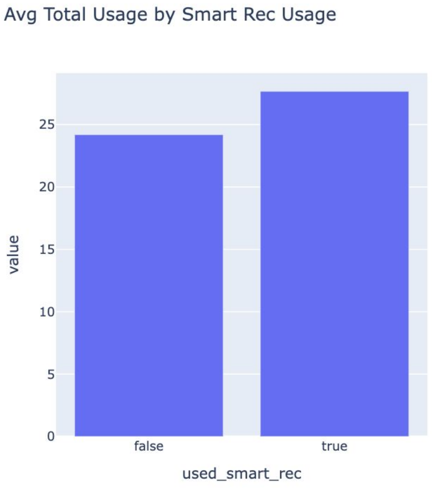
🚦 Metric	Value	Status
Smart Rec Adoption Rate	96.9%	🟢
Avg. Smart Rec Share of Usage	54.95%	🟢
Avg Smart Rec Usage (users who used it)	15.32	🟡
Avg. Total Usage (Smart Rec Users)	27.66	🟡
Avg. Total Usage (Non-Users)	24.19	
Avg. Tenure (Smart Rec Users)	87.83	🟡
Avg. Tenure (Non-Users)	81.45	
Smart Rec Users	**969**	
# Non Smart Rec Users	**31**	🔴 (small sample)

- Adoption is near-universal (97%).
- Smart Rec users show higher usage and retention, but the non-user group is too small for statistical certainty.

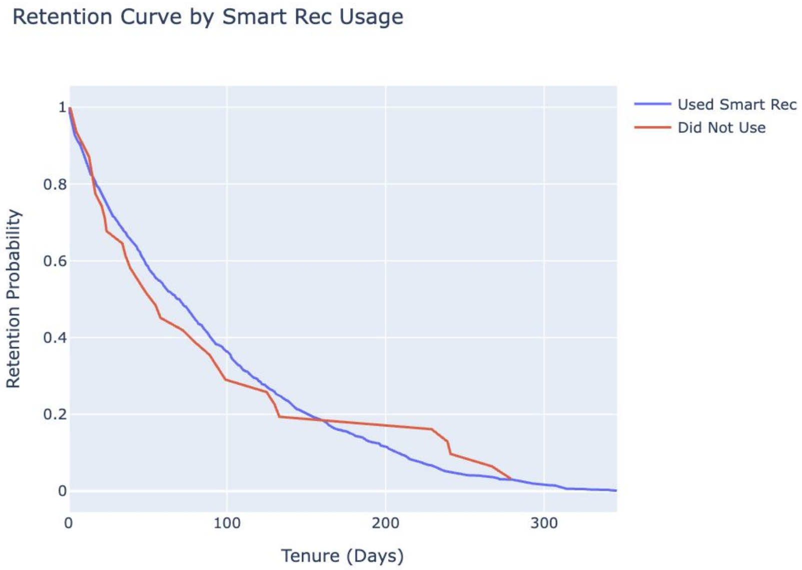
So what?

- Adoption of Smart Recommendation is almost universal, providing a strong foundation for analysis.
- While engagement and retention are higher for feature users, the small non-user group means future product decisions should be supported with further experimentation.

Product Impact & Statistical Findings



T-test: t=1.68, p=0.1024 | Cohen's d: 0.34
⚠️ Difference is not statistically significant

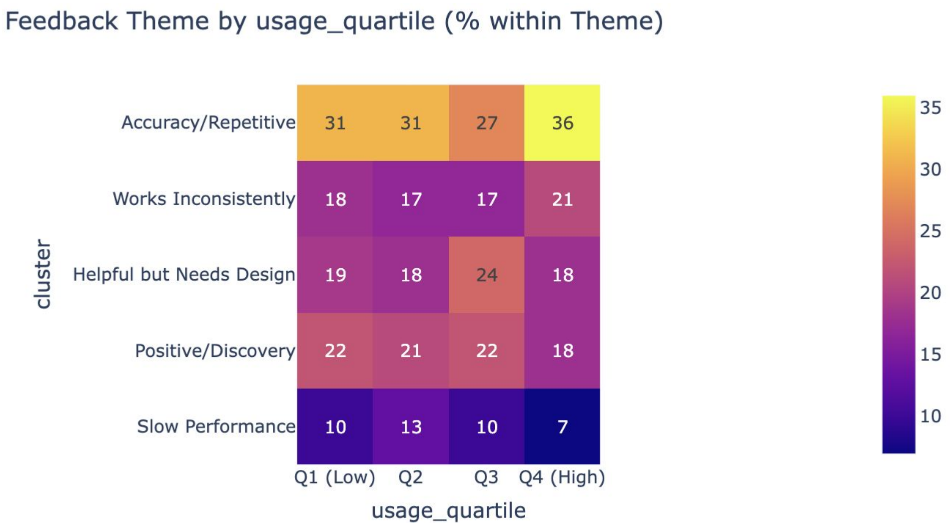


- Smart Rec users: +14% usage, longer retention, higher satisfaction.
- Uplift is not statistically significant (p=0.10) due to small non-user group.

So what?

- Early signs are positive:
  - Smart Rec users are more active and engaged.
- However, statistical confidence is limited—directional, not definitive—making experimentation and larger-scale monitoring a priority.

Qualitative Feedback Analysis



So what?
User feedback pinpoints the most valuable opportunities for product and UX improvement—especially reducing irrelevant recommendations, clarifying the interface, and speeding up feature performance.

Theme 1 – Accuracy/Repetitive
1. I like the recommendations, but sometimes they are not accurate.
2. The recommendations seem repetitive. I wish there was more variety.
3. I don't see much value in the recommendations. They don't match my interests.

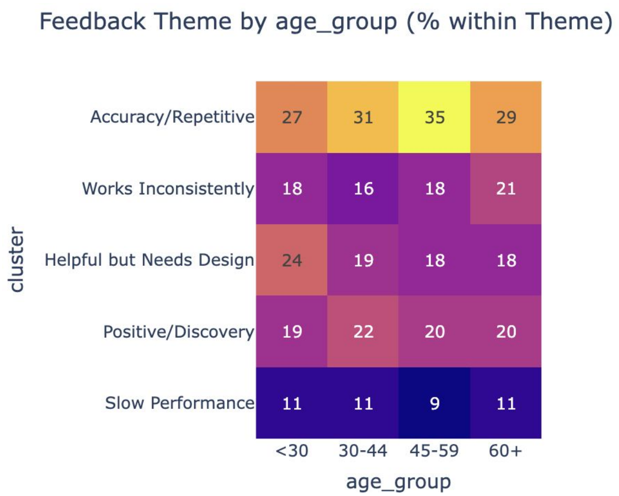
Theme 2 – Works Inconsistently
1. The feature is interesting, but it doesn't always work as expected.
2. It's a great feature, but it could use some fine-tuning to make it more accurate.

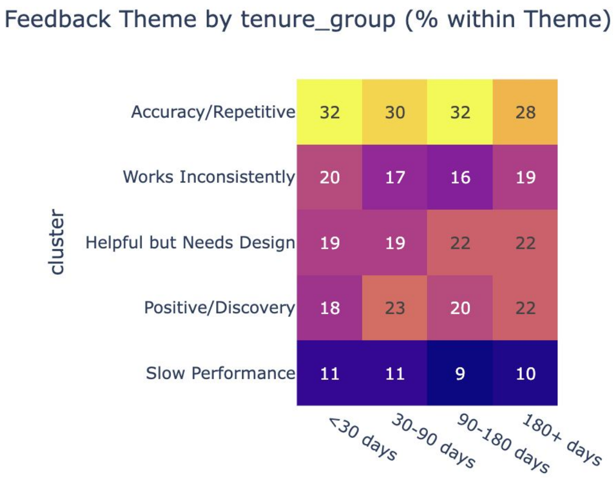
Theme 3 – Helpful but Needs Design
1. The recommendations are helpful, but the design could be improved.
2. The recommendations are good, but the interface could be more user-friendly.

Theme 4 – Positive/Discovery
1. The Smart Recommendation feature has really improved my experience with the app.
2. The Smart Recommendation feature is amazing! I've discovered so many new things.

Theme 5 – Slow Performance
1. The feature is helpful, but it takes too long to load.

Segment Insights & UX Risks





- Users 45–59 most likely to complain about rec accuracy; UI/design pain points span all ages.

- Design issues flagged by longer tenure users (90D+)

So what?

- Segment analysis reveals where specific pain points may be driving disengagement.
- Addressing accuracy and design complaints among middle-aged and longer-tenure users can improve overall retention.

Recommendations & Experiment

- Upgrade personalization algorithm to reduce irrelevant recommendations.
- **Prioritize qualitative/user research for the 30–59 segment** to uncover and remove barriers to higher daily engagement.
- A/B test onboarding, nudges, and personalization for problematic groups.
- UI and performance improvements.
- Add structured feedback (👍👎) to collect more actionable user input.
- **A/B/C Experiment:** Control: current UI; Variant A: prominent UI + tooltip; Variant B: improved logic + tooltip.
- **KPIs:** Adoption, engagement, satisfaction, retention.

Limitations & Next Steps

- **Limitations:**
    - Feedback duplication; small control group.
    - NLP results are directional, not robust.
- **Next Steps:**
    - Improved feedback data, cohort tracking, experiment implementation.

Thank you!

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