Gmail

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RFM Analysis Overview - Power User Segmentation

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Hi Team,

As part of our efforts to identify Fetch's power users, we've launched our RFM (Recency, Frequency, Monetary) initiative. This approach helps us understand our best customers by analyzing how recently they've made purchases, how often they engage with the app, and how much they spend. Below is a summary of the RFM metrics we've used for segmentation:

Metric	Definition
Recency	# of days since last receipt scanned
Frequency	# of unique receipts scanned
Monetary	Total sum of revenue from user transactions

Each of these metrics is divided into three buckets and scored from 1 to 3, where 1 represents the best performance. These scores are then summed to produce a cumulative score (k), which is used to classify customers into the following segments:

Segmentation	Cumulative Score (k)
High	≥ 8
Medium	6 - 7
Low	< 6

Key Insights from RFM Analysis:

- **Direct Revenue Insight**: The *Monetary* metric provides direct insight into the value users contribute through their spending, helping us prioritize high-revenue users.
- **High-Value User Identification**: RFM analysis highlights the most valuable customers, including those who frequently engage or make large purchases. This allows Fetch to focus on the users who drive the most value.
- **Targeted Marketing**: With the RFM scores, we can better target high-scoring users with tailored marketing campaigns, such as loyalty programs or exclusive offers, to retain and further engage them.
- **Comprehensive Engagement Tracking**: By examining all three metrics—*Recency, Frequency, and Monetary*—we gain a well-rounded understanding of user behavior, helping us identify both highly engaged and high-spending customers.

Potential Biases:

- **Monetary Bias**: Users who purchase fewer, but higher-value items may score higher in the *Monetary* category, even if their engagement is not as high. This could skew results by prioritizing high spenders over more engaged users.
- **Inconsistent Spending Patterns**: Some users might make infrequent but large purchases, which could place them in a high *Monetary* category despite lower overall engagement, potentially misrepresenting their loyalty.
- **Excluding Non-Revenue Users**: Users who engage heavily but do not contribute to revenue (e.g., those who use app features without making purchases) may be undervalued or overlooked in this analysis.

Request for Action:

To improve the accuracy of our analysis and address any potential biases, I would appreciate further discussion on the following:

1. **Non-Revenue Users**: Should we consider users who engage with the app but don't directly contribute to revenue (e.g., users who use features but don't make purchases)? Including them could provide a more complete view of overall engagement.
2. **Revenue Attribution**: To ensure accurate insights, it would be helpful to confirm that revenue is properly attributed, especially for users who engage with app features linked to promotional efforts or special offers.
3. **Data Completeness**: While the data cleaning process handles empty values and formatted dates appropriately, we should ensure that all records are consistently processed. Specifically, transactions without final sales, such as refunds or failed transactions, need to be handled appropriately to avoid skewing the *Monetary* metric.

Looking forward to your thoughts on these points!

Best regards,

Selvyn Martinez Barahona, Data Analyst