# Detailed Report

**TravelTide – Customer Segmentation and Perk Strategy**

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## 1. Background and Business Context

TravelTide has experienced rapid growth by prioritizing product breadth and search excellence, offering one of the largest travel inventories in the market.
While this strategy has successfully driven acquisition, customer retention has remained underdeveloped.

To address this gap, the company is exploring a personalized rewards program aimed at encouraging repeat usage and increasing conversion.
Rather than offering uniform incentives, the objective is to understand **which perk matters most to each customer**, and to use that insight to personalize rewards communication.

The core challenge is therefore not deciding *which* perks to offer, but **how to assign them in a way that increases conversion and retention without amplifying cancellation risk or eroding margins**.

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## 2. Objectives and Analytical Scope

This analysis was designed to answer two core business questions:

1. Can TravelTide reliably match each user to **a single, targeted perk** based on behavioral evidence?

2. Can this personalization improve conversion and retention **without increasing cancellation risk or margin erosion**?

To remain decision-focused, the scope of the analysis explicitly excludes:

- demographic-only targeting,
- dynamic pricing or discount optimization,
- black-box personalization models without business control.

The goal is a **transparent, interpretable, and scalable framework** suitable for operational deployment.

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## 3. Data and Cohort Definition

The analysis integrates session-level and user-level data across four relational tables: sessions, users, flights, and hotels.

Before segmentation, the data model and trip lifecycle were validated to ensure semantic consistency.
Sessions were classified into browsing, booking, and cancellation events, allowing cancellations to be treated as a **behavioral signal** rather than noise.
This step ensured that downstream insights reflect genuine customer behavior rather than artifacts of data structure or timing.

Following guidance from the Head of Marketing, the cohort was defined as:

- users with sessions occurring after **January 4th, 2023**, and
- users with **more than seven sessions** within the same time window.

This cohort balances behavioral depth with comparability, excluding one-off or inactive users while preserving sufficient signal to support reliable segmentation.

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## 4. Behavioral Framework

User behavior consistently organizes around four stable dimensions, which form the foundation of the segmentation framework.

**Value** captures economic intensity rather than frequency.
High value is often generated by infrequent but expensive and complex trips, not by repeated low-cost bookings.

**Risk** reflects cancellation behavior as a signal of uncertainty.
Cancellations are highly unevenly distributed and concentrate in specific behavioral profiles rather than occurring randomly.

**Complexity** describes trip structure, including duration, number of components, and logistical burden.
More complex trips tend to generate higher spend but also higher fragility.

**Engagement** captures activity level and interaction intensity, but does not necessarily imply commitment.
Highly engaged users are not always decisive, while some low-engagement users exhibit near-perfect follow-through.

Separating these dimensions avoids collapsing distinct behaviors into a single score and enables targeted intervention.

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## 5. Segmentation and Validation

Segmentation follows a hybrid approach.

A **rule-based framework** assigns users to segments using explicit eligibility and priority rules derived from the four behavioral dimensions.
This approach ensures transparency, interpretability, and business control, including the constraint that **each user receives exactly one perk**.

Unsupervised clustering is used solely as a validation layer.
Without using predefined personas or perks, the data naturally separates into four stable behavioral archetypes that align closely with Value, Risk, Complexity, and Engagement.

This alignment confirms that the segmentation logic reflects real behavioral structure rather than arbitrary rules.

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## 6. Perk Strategy Logic

Perks are treated as **friction-removal tools**, not generic rewards.

Each perk addresses a specific behavioral need:

- reassurance for high-value but fragile trips,
- logistical support for complex travel,
- experience enhancement for hotel-centric users,
- activation for low-engagement but reliable users.

Risk exposure is explicitly controlled through eligibility conditions and exclusions.
High-risk users are not exposed to price-based incentives, and reassurance-based perks are gated by proven follow-through.

Assigning exactly one perk per user ensures clarity in communication and prevents incentive stacking or cost escalation.

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## 7. Recommendations and Next Steps

**Implement the proposed perk assignment framework.**
The strategy is behavior-driven, interpretable, and validated by independent clustering.

**Treat high-value, high-risk users as a controlled growth segment.**
Selective reassurance can unlock value while keeping downside capped.

**Avoid blanket discounts.**
Price-based incentives should remain limited to low-risk users with demonstrated reliability.

**Test and iterate through controlled experiments.**
Measure uplift in conversion, retention, and cancellation before scaling.

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## 8. Conclusion

This project demonstrates that effective personalization is not about offering more incentives, but about **offering the right intervention at the right moment**.

By focusing on behavioral friction rather than demographics or volume, TravelTide can deploy a rewards strategy that improves conversion, protects value, and scales sustainably.