Request For Problem

Organisation: Deloitte

Topic: Customer Segmentation Using Big Data in Retail

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1. Background

1.1 Industry and Company Overview

The credit card industry is one of the fastest-growing parts of retail banking and financial services in India and around the world. With rising consumer desires, growing digital use, and more online shopping, credit cards have become more than just a payment tool. They now act as a financial lifestyle product that combines convenience, access to credit, and loyalty benefits.

In India, credit card usage is still quite low compared to developed countries. Less than 7% of the population uses credit cards, while countries like the US have usage rates above 65%. This gap shows a big opportunity for banks, non-banking financial companies (NBFCs), and fintech firms to grow their cardholder base. However, with growth comes the challenge of managing credit risk. Rising defaults and non-performing assets (NPAs) can significantly threaten the financial stability of banks.

Historically, banks have divided credit card customers based on income, job type, and credit bureau scores, like CIBIL in India. While these factors help assess eligibility, they do not fully reflect a customer's financial habits, repayment behavior, or changing risk profile over time. This creates inefficiencies where:

- Safe customers receive lower credit limits or fewer rewards despite consistent repayment behavior.
- Risky customers get higher limits than they can responsibly manage, increasing the risk of defaults.

Data-driven customer segmentation and predictive modelling are essential in this context. By examining demographic data, such as age, income, region, and occupation, alongside behavioural data like spending habits, utilization ratio, and repayment discipline, banks can develop a more accurate and flexible understanding of their customers.

The company in question, whether a bank or card issuer, is competing in a market where new fintech startups are providing real-time, personalized credit products. To stay competitive and secure, the company needs to use analytics-based segmentation and forecasting systems.

1.2 Statement of Purpose (Scope of Work)

This project's aim is to create and implement a strong customer segmentation framework for credit card users, backed by predictive and prescriptive analytics. Unlike traditional methods that stick to static classifications, this system will offer ongoing, data-driven insights into customer behavior, risk, and future usage.

The scope of work includes:

- Data Preparation & Integration: Combining financial transaction data with demographic data into a single, clean dataset.
- Feature Engineering: Developing new behavioral indicators like:
  - Utilization Ratio (Balance ÷ Credit Limit),
  - Repayment Discipline (full payments vs. minimum dues),
  - Cash Advance Dependency (cash withdrawals compared to purchases).

- Segmentation: Grouping customers into distinct personas:
    - Safe High Spenders,
    - Moderate Users,
    - Revolvers (those who carry forward balances),
    - Over-Leveraged Customers.
- Predictive Modeling: Running simulations and forecasting customer behavior under stress scenarios, like interest rate increases or drops in repayments.
- Prescriptive Strategy: Suggesting credit management actions such as:
    - Upgrading safe customers to higher limits and better offers,
    - Limiting risky customers to prevent defaults,
    - Adjusting APRs (interest rates) fairly across customer groups.

The main goals of this work are twofold:

- For Banks and Retailers: To lower credit risk, avoid NPAs, and boost revenue by better targeting products and services.
- For Customers: To ensure fair, personalized credit allocation that aligns with their actual behavior and needs, enhancing satisfaction and trust.

In summary, this project changes segmentation from a static, compliance-focused task into a dynamic business strategy that balances risk management with growth opportunities.

2. Problem Framing

2.1 Broader Description of the Problem

Credit cards are meant to be convenient. They allow people to buy now and pay later, while also helping banks earn money from fees and interest. However, the challenge lies in finding balance. If a bank gives too much credit to the wrong customer, it risks non-payment, which leads to non-performing assets. On the other hand, if it gives too little credit to a reliable customer, it loses potential revenue and frustrates that customer.

Historically, many issuers depend on a few static checks - like income, city tier, and a score from bureaus like CIBIL - mostly at the time of card issuance. These checks are helpful but fail to reflect how customers actually behave after they start using their cards. People's circumstances can change. They may increase spending, change jobs, face varying interest rates, or encounter emergencies. Without a continuous, behavior-aware perspective, banks often react too late. They recognize risks only after payments are missed and miss chances to reward good customers until those customers leave or stop using their cards.

In short, the main issue is the disconnect between how credit is allocated and how customers genuinely use and repay that credit over time.

2.2 Situation Analysis

To identify where problems arise and where improvements can be made, it helps to examine the entire data and decision process throughout the customer lifecycle.

Today's reality at onboarding, banks approve or reject applications based on a score and income proof and set an initial limit using fixed rules. This might involve giving 2 to 3 times the monthly income as a credit limit.

After the card is issued, monitoring is mostly reactive. Limit changes occur infrequently, typically every 6 to 12 months, and often through manual campaigns.

Some signals go unnoticed or are delayed: early warning signs - like rising utilization, a shift from paying full dues to minimum payments, and frequent cash withdrawals - are not consistently acted upon.

Uniform policies are applied across very different customers, meaning some reliable customers are capped while some risky customers are overexposed.

What the data actually contains, beyond income and a CIBIL score, card systems already capture valuable behavior:

- Utilization Ratio (balance ÷ credit limit) indicates how stretched a user is.
- Repayment Discipline (how often full dues are paid versus minimums) demonstrates intent and ability to repay.
- Cash Advance Dependency (cash withdrawals versus purchases) can reveal short-term issues.
- Purchase patterns (frequency, categories, spikes) show lifestyle and stability.
- Tenure and demographics (age, occupation, city tier) provide context.

Observed patterns (typical across portfolios):

- A group of Safe High Spenders regularly uses their cards, pays on time, and can safely handle higher limits.
- Moderate Users are stable but not fully engaged; appropriate nudges can increase their usage.
- Revolvers carry balances and regularly pay interest - increasing revenue but also presenting higher risks if conditions worsen.
- Over-leveraged customers show high utilization, missed or late payments, or heavy cash advances; this is where future non-performing assets are likely to concentrate.

The issue is not the lack of data; it is turning these signals into timely and understandable decisions.

2.3 Problem Definition

How can we match credit policy to actual customer behavior dynamically? We want to safely grow revenue while reducing default risk, using a framework that is clear, fair, and easy to manage.

Specifically, we need to:

- Continuously segment customers based on behavior (utilization, repayment, cash advances), enhanced with demographic information.
- Predict how these segments will behave if conditions change, such as interest rate increases or reductions in repayments.
- Recommend actions - like limit increases or decreases, APR adjustments, and precautionary outreach - based on risk and value, ensuring the rules remain simple enough for business teams to understand and for auditors to review.

2.4 Project Objectives

To address the defined problem, the project will create a complete, business-ready approach:

i. Build an integrated data foundation.

Merge transactional and demographic data, address missing values, standardize key fields, and develop easy-to-understand features (Utilization Ratio, Repayment Discipline, Cash Advance Dependency). The aim is to create a reliable "single source of truth" for credit decisions.

ii. Create explainable customer segments.

Group customers into categories - Safe High Spenders, Moderate Users, Revolvers, Over-leveraged - so that Risk, Marketing, and Operations can share the same language and act consistently. (Image 1)

iii. Run predictive stress tests.

Simulate various scenarios (like a 200-basis points interest rate increase or a 15% reduction in repayments) to see where risk will rise first and by how much, assessing customer, segment, and region levels. (Image 2)

iv. Translate insights into actions.

Design a clear policy engine that links segment and risk signals to decisions:

- Increase limits or decrease APR for disciplined, under-utilized customers.
- Maintain or reduce limits and/or tighten terms for over-leveraged or deteriorating profiles.
- Targeted engagement (such as education or payment plans) where behavior indicates temporary distress.
- Turn these results into operational tables so CRM teams can act quickly.

v. Governance, fairness, and explainability.

Implement simple thresholds and audit trails to ensure decisions are consistent across income levels and geographic areas, making them easy to justify to customers and regulators.

What success looks like:

- Fewer surprises through early risk detection.
- More revenue from reliable customers via timely limit increases and relevant offers.
- A lower trend of non-performing assets through preventive actions taken before delinquency occurs.
- Clear, fair, and understandable credit decisions that build trust with customers.

3. Project Execution

The execution method follows a clear and dependable process:

- a framework that explains why the approach works,
- a solid data foundation that ensures results are reliable, and

- an analysis layer that turns signals into actions.

3.1 Conceptual Framework of the Study

Why a new approach is needed. Traditional credit card decisions rely on fixed checks (income, city, credit bureau score) mainly at issuance. However, customer behaviour changes over time - spending may rise or fall, repayment habits can shift, and economic conditions fluctuate. An effective system needs to recognize these changes early and react accordingly.
The three-layer framework:

i. **Descriptive (What is happening?)**

Break down complex behaviour into a few easy metrics:

- Utilization Ratio = Balance ÷ Credit Limit → How much the customer is using their credit.
- Repayment Discipline = Full-payment frequency / consistency of paying more than the minimum due → Ability and willingness to pay back.
- Cash Advance Dependency = Cash Advance ÷ Purchases → Signal of short-term financial stress.
- Combine these with customer context (age, income band, city tier, region, tenure) to create clear personas: Safe High Spenders, Moderate Users, Revolvers, Over-leveraged.

ii. **Predictive (What may happen next?)**

Conduct stress tests to simulate changes - for example, a +200-bps interest-rate increase or a –15% drop in repayments - and estimate how balances, utilization, and risk will change by persona and location. This transforms "**surprise risk**" into "**visible risk**".

iii. **Prescriptive (What should we do?)**

Translate signals into straightforward rules business teams can follow:

- Increase limits or lower APR for responsible, under-utilized customers.
- Hold or tighten limits for those with worsening profiles (high utilization, deteriorating repayment, cash dependency).
- Offer assistance through outreach, reminders, or short payment plans for customers showing temporary difficulties.
- Each action is explainable and documented (what threshold led to which decision).

Core principles: keep indicators simple, make decisions clear, and check fairness across income bands and regions.

3.2 Identification of Data Source and Data Collection

a. Data sources:

i. Credit Behaviour (cc_general.csv)

- Key fields typically include BALANCE, CREDIT_LIMIT, PURCHASES, ONEOFF_PURCHASES, INSTALLMENTS_PURCHASES, CASH_ADVANCE, PAYMENTS, MINIMUM_PAYMENTS, PRC_FULL_PAYMENT, TENURE, and various frequencies/counts.
- These fields allow us to calculate the three main behavioural indicators: Utilization Ratio, Repayment Discipline, and Cash Advance Dependency.

ii. Demographics (credit_card_demographics.csv)
- CUST_ID with age, gender, income band, education, occupation, marital status, city tier/region, home ownership, dependents, and more.
- This context helps explain why different segments behave differently (e.g., city-tier or income-band effects).

b. Data preparation pipeline:

- Ingest: Load both files as-is; maintain source and timestamps.
- Clean:
  - Standardize formats (numeric types, date formats, percentage scales).
  - Address missing values (e.g., set MINIMUM_PAYMENTS nulls to policy defaults; drop clearly incorrect rows).
  - Cap extreme outliers where necessary (to prevent a few records from skewing averages).
- Feature-ready:
  - Calculate UTILIZATION_RATIO = BALANCE / CREDIT_LIMIT (guard against division by zero).
  - Determine REPAYMENT_DISCIPLINE using PRC_FULL_PAYMENT (or derive from PAYMENTS vs MINIMUM_PAYMENTS when necessary).
  - Calculate CASH_ADVANCE_DEP = CASH_ADVANCE / PURCHASES (ensure safe treatment when PURCHASES = 0).
  - Create tenure groups, income bands, and region labels for profiling.
  - Maintain a data dictionary and lineage so every feature can be traced back to its source.

  Privacy & governance: use hashed IDs; keep PII separate with limited access; store validation checks (e.g., UTILIZATION in [0, ~1.5], PAYMENTS ≥ 0).

3.3 Analysis of Data

Below is a summary of the analysis, using the attached spreadsheets and your compiled SQL outputs for the same population.

a. Descriptive Segmentation:

How we segment (simple thresholds, easy to explain): (Image 3)

- Safe High Spenders: Generally, use < 40% of their credit and show high repayment discipline (frequent/full payments).
- Moderate Users: Have mid-range utilization (around 40–70%) with stable payments.
- Revolvers: Often carry balances or only make minimum payments; utilization usually > 70% or persistently low full-pay.
- Over-leveraged: Exhibit very high utilization (usually > 90%) with poor or declining repayment.

What the data shows:

- Segment counts from your SQL results: (Image 4)
  - Moderate Users: 4,475 customers; average utilization ≈ 32%; full pay ≈ 11.6%.
  - Revolvers: 3,147 customers; average utilization ≈ 64.5%; full pay ≈ 0.9%.
  - Safe High Spenders: 1,328 customers; average utilization ≈ 1.5%; full pay ≈ 62.5%.

  - Over-leveraged customers are included within high-risk/Revolver tails in the SQL roll-up; when explicitly analysed, they form the riskiest subset of Revolvers.

Why this matters:

- Safe High Spenders are dependable and under-leveraged - there's room for growth through limit upgrades and APR reductions.
- Revolvers generate revenue (interest) but are at risk - controlling risk is crucial to prevent future defaults.
- Moderate Users can be encouraged towards higher engagement without significantly increasing risk - balanced growth.

Lifecycle and revenue indicator:

- Early-tenure (0–12 months) customers already show strong spending and revenue indicators (e.g., Moderate Users average around 1387 purchases; notable portfolio contribution). This supports strong onboarding and early upgrades for responsible users. (Image 5&6)

Income is not destiny:

- Both high-income (₹20L+) and low-income (<₹5L) bands had ~39 - 40% utilization with ~14 - 15% full-pay on average.
- Implication: behaviour - not income alone - should drive segmentation and policy.

b. Predictive Stress Testing (anticipating tomorrow's risk):

Scenarios used (level stress):

- Rate shock: +200 bps interest.
- Repayment shock: -15% full-payment rate (more customers rolling balances).
- Combined shock: rate + repayment.

Observed impacts:

- Average utilization increased from ~47.4% to ~57.0% under stress.
- Average risk score shifted around 0.545 (evidence of meaningful decline).
- Revolvers experienced the greatest increase in stress, indicating they are the first to slip into delinquency.
- Geographic hotspots: Rural/Semi-Urban East showed higher risk (average risk ≈ 0.56), guiding targeted actions.

Why this matters:

- Stress tests reveal "hidden" risk before delinquency occurs.
- The bank can proactively limit exposure in hotspots, hold off on upgrades for vulnerable segments, or reach out to at-risk customers.

c. Prescriptive Policy & Actioning (turning insight into decisions)

Rules the business can implement (examples): (Image 7)

- Upgrade (growth): If Utilization < 40% and strong full-payment history for the last 6 months → increase limit by 10 - 20%; consider lowering APR by 50 to 75 bps.

- Hold (monitor): If 40 - 70% utilization with stable payments → no limit change; monitor monthly.
- Tighten (contain risk): If > 70 - 90% utilization or rising cash advances or 2+ months of late/minimum payments → freeze/reduce limit; increase APR by 50 to 100 bps; initiate outreach for assistance.
- Assist (retain & cure): If sudden drop in performance after a long, good history → offer a payment plan and financial education.

Scale of impact (from SQL outputs):

Out of ~8,950 analysed customers:

- 5,443 (~60%) → No change (status quo is appropriate).
- 2,798 (~31%) → Limit reductions proposed (average risk ≈ 0.83).
- 709 (~9%) → Limit upgrades proposed (average risk ≈ 0.32).
- APR adjustments remained fair across income bands: safe segments saw average APR reductions (~ -65 bps); risky segments faced APR increases (~+70 bps)—transparent and regulator-friendly.

Operationalization:

- Export recommendations as CRM - ready action tables (Customer ID, action, rationale).
- Conduct a monthly governance review to adjust thresholds and ensure fairness.

4. Results and Findings

4.1 Proposed Solution & Justification

The project's solution aimed to turn raw financial and demographic data into actionable steps through three stages: segmentation, stress forecasting, and prescriptive recommendations.

Segmentation Findings

- Customers were divided into three main groups: (Fig. i)
  - Moderate Users (4,475 customers): average utilization at 32%, very low full-pay rate at 11.6%.
  - Revolvers (3,147 customers): highest average utilization of 64.5%, with almost no full-pay behaviour at 0.9%.
  - Safe High Spenders (1,328 customers): very low utilization at 1.5% but strong repayment discipline, with a full-pay rate of 62.5%.

This segmentation reveals clear business personas. Revolvers carry high risk, Moderate Users are balanced but not very engaged, and Safe High Spenders are dependable but underutilized by banks.

Lifecycle Profitability

New customers (0 - 12 months) are already profitable:

- Moderate Users generated an average of 1,387.2 units purchased, resulting in a revenue estimate of ₹93,115.56.
- Safe High Spenders made an average of 799.04 purchases, offering additional revenue potential.

This highlights the significance of onboarding campaigns during the first year.

Income Behaviour Analysis

Across income levels:

- High earners (₹20L+) had a utilization rate of 39% with only a 15% full-pay rate; this shows even wealthy customers carry risk.
- Lower-income customers (<₹5L) displayed about 39.5% utilization with a 14.2% full-pay rate, indicating they are also risky.

Thus, repayment discipline does not depend solely on income, emphasizing the need for behavioural segmentation in addition to income-based rules.

Stress Forecasting

When applying stress scenarios (+200 bps interest, -15% repayment):

- Average utilization rose from 47.4% to 57%.
- Risk scores increased to an average of 0.545, with Revolvers being more severely impacted.
- Geographic risk heatmaps showed that Rural East (average risk of 0.565) and Semi-Urban East (average risk of 0.562) were key hotspots.

This provides early signs of where and when non-performing assets may increase.

Prescriptive Recommendations

From approximately 8,950 customers analysed:

- 5,443 (60%) showed no change in credit policy.
- 2,798 (31%) had proposed limit reductions (average risk = 0.829).
- 709 (9%) had proposed limit upgrades (average risk = 0.323).

APR ladder analysis confirmed fairness:

- Safe High Spenders received APR cuts averaging a decrease of 65 bps.
- Revolvers faced APR increases averaging an increase of 70 bps across income brackets.

This ensures compliance with regulations and fairness for customers.

The solution is feasible because:

- It uses existing data, eliminating the need for new costly systems.
- It yields understandable rules, making it easy for risk and marketing teams to implement.
- It balances growth and risk by upgrading safe customers while managing high-risk groups.

5. Conclusion

The project successfully transformed raw transaction and demographic data into a clear framework for dynamic credit segmentation, stress testing, and prescriptive strategies.

Findings indicate that:

- Safe High Spenders are a missed opportunity for growth through limit upgrades and lower APR.

- Revolvers pose the highest risk, especially in stressed conditions, requiring tighter credit measures and educational programs.
- Geographic hotspots (East, Semi - Urban, and Rural areas) need targeted interventions.

This dual approach of rewarding disciplined customers and managing risky ones creates a balanced portfolio strategy.

5.1 Recommendations

a. Targeted Growth Campaigns
   - Focus upgrades and APR reductions on Safe High Spenders and low-risk Moderate Users.
   - New customers should receive better onboarding offers to build loyalty.

b. Risk Mitigation in Revolvers
   - Implement tighter credit limits and higher APRs for high-risk Revolvers.
   - Combine these measures with debt restructuring or literacy programs to avoid defaults.

c. Geographic Interventions
   - Rural and Semi-Urban East areas show the highest risk.
   - Introduce micro-credit products or education initiatives tailored to those regions.

d. Lifecycle-Driven Engagement
   - Strengthen onboarding campaigns for first-year customers since those aged 0-12 months already provide high revenue.

e. Fairness and Compliance
   - Regularly check APR ladder adjustments across income bands to maintain transparency and avoid bias.

5.2 Limitations

i. Data Scope - The analysis used historical transaction and demographic data; it did not include real-time streaming data.

ii. External Shocks - Factors like pandemics or regulatory changes were not considered, but they can significantly impact repayment.

iii. Behavioural Complexity - Ratios oversimplify customer behaviour. Deeper psychological and macroeconomic factors (job loss, inflation, etc.) are not directly modelled.

iv. Model Generalization - Findings may need adjustments for different banks, regions, or customer pools.

Annexure

A. Images and Tables for Reference

Image. 1:

```
CREATE OR REPLACE VIEW segmentation_v AS
SELECT
  *,
  CASE
    WHEN UTILIZATION_RATIO < 0.40 AND COALESCE(REPAYMENT_DISCIPLINE,0) >= 0.50
      THEN 'Safe High Spenders'
    WHEN UTILIZATION_RATIO > 0.90 AND COALESCE(REPAYMENT_DISCIPLINE,0) < 0.05
      THEN 'Over-Leveraged'
    WHEN UTILIZATION_RATIO BETWEEN 0.40 AND 0.70 AND COALESCE(REPAYMENT_DISCIPLINE,0) >= 0.10
      THEN 'Moderate Users'
    WHEN UTILIZATION_RATIO > 0.70 OR COALESCE(REPAYMENT_DISCIPLINE,0) < 0.10
      THEN 'Revolvers'
    ELSE 'Moderate Users'
  END AS SEGMENT
```

Image 2:

```
CREATE OR REPLACE VIEW stress_scenarios_v AS
WITH base AS (
  SELECT
    CUST_ID, SEGMENT, GEO_BUCKET, INCOME_BAND,
    UTILIZATION_RATIO AS BASE_UTIL,
    COALESCE(REPAYMENT_DISCIPLINE,0.0) AS BASE_REPAY
  FROM segmentation_v
),
params AS (
  SELECT 0.15 AS repay_drop, 0.20 AS util_sensitivity -- 15% repay drop; add 0.2*0.15 to util
),
stressed AS (
  SELECT
    b.*,
    -- repayment falls; floor at 0
    GREATEST(b.BASE_REPAY - p.repay_drop, 0.0) AS STRESSED_REPAY,
    -- utilization rises modestly due to lower repayments; cap at 2.0 (200%)
    LEAST(b.BASE_UTIL + (p.repay_drop * p.util_sensitivity), 2.0) AS STRESSED_UTIL
  FROM base b
  CROSS JOIN params p
)
SELECT *,
  -- simple composite risk: more weight on utilization than repay drop
  ROUND(0.6*STRESSED_UTIL + 0.4*(1.0 - STRESSED_REPAY), 4) AS STRESSED_RISK
FROM stressed;
```

Image 3:

```
SELECT SEGMENT,
       ROUND(AVG(UTILIZATION_RATIO),3)    AS AVG_UTIL,
       ROUND(AVG(REPAYMENT_DISCIPLINE),3) AS AVG_REPAY,
       ROUND(AVG(CASH_ADVANCE_DEP),3)     AS AVG_CASH_DEP
FROM segmentation_v
GROUP BY SEGMENT
ORDER BY SEGMENT;
```

Image 4: (Output)

SEGMENT	AVG_UTIL	AVG_REPAY	AVG_CASH_DEP
Moderate Users	0.141	0.247	577.664
Over-Leveraged	0.972	0	1.801
Revolvers	0.408	0.01	160.632
Safe High Spenders	0.043	0.817	0.254

Image 5:

```
SELECT SEGMENT, COUNT(*) AS CUSTOMERS
FROM segmentation_v
GROUP BY SEGMENT
ORDER BY CUSTOMERS DESC;
```

Image 6:

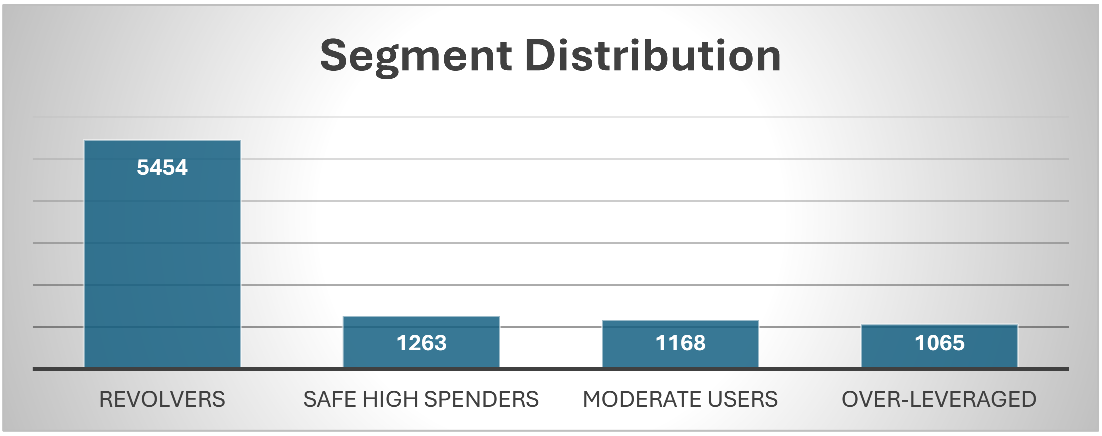
SEGMENT	CUSTOMERS
Revolvers	5454
Safe High Spenders	1263
Moderate Users	1168
Over-Leveraged	1065

Image 7:

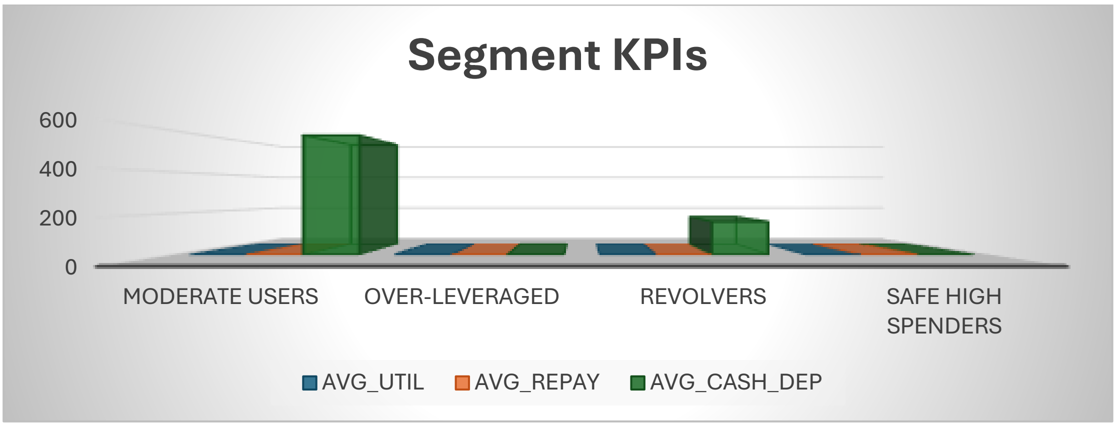
ACTION_CODE	CUSTOMERS
TIGHTEN_LIMIT / APR_HIKE	6519
UPGRADE_LIMIT / APR_CUT	1263
ASSIST_OUTREACH	1028
HOLD_MONITOR	140

B. Figures

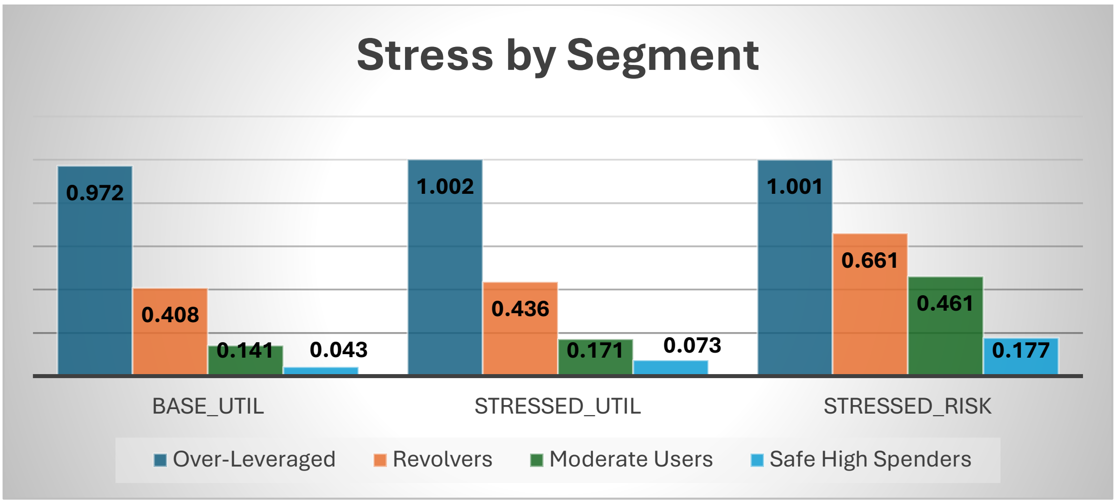
i. Segment Distribution Bar Chart



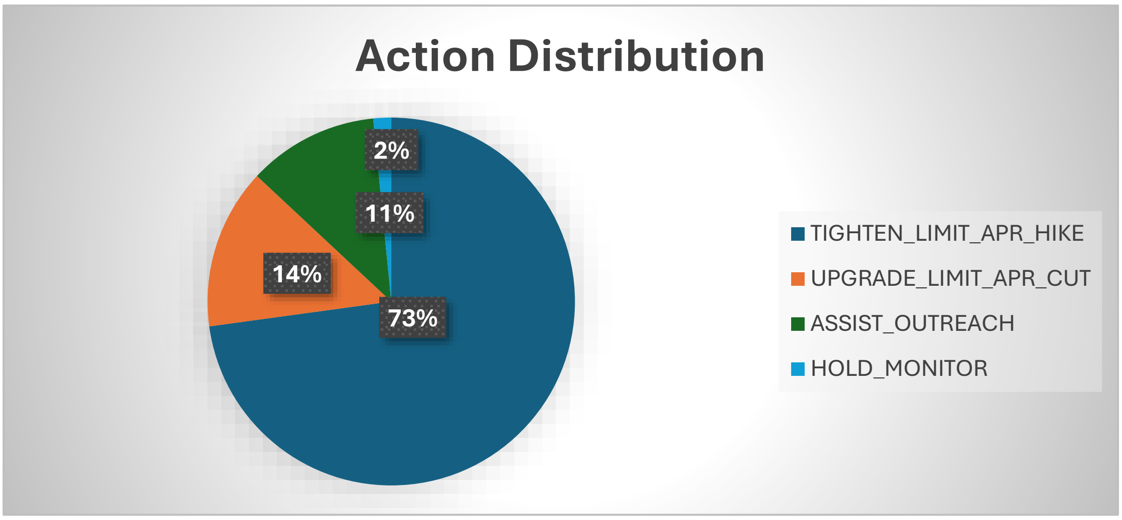
ii. **Segment KPIs Bar Chart**



iii. **Stress by Segment Clustered Bar Chart**



iv. **Actions by Segments Pie Chart**



Name – ANKITA ANAND
Reg. No – 2024JULB00232
Major – Digital Business and Analytics / **Minor** – Finance
RFP Company – Deloitte
RFP Mentor – Prof. Sundar Raj Vijayanagar
Major Contribution to the project: She worked on the research and documentation part of the project. She studied relevant academic papers and market reports to strengthen the project framework. She also prepared detailed background sections, problem statements, and linked findings with real-world banking practices, ensuring the report had both depth and clarity.

Name – SARASWATI GOWDA
Reg. No – 2024AUGVPGP0029
Major – Digital Business and Analytics / **Minor** – Marketing
RFP Company – Deloitte
RFP Mentor – Prof. Sundar Raj Vijayanagar
Major Contribution to the project: She designed the visual outputs of the analysis. She created dashboards and charts showing customer segments, key performance indicators, and stress test results. Her visualizations made the data easy to understand and helped present complex insights clearly during the group's final presentation.

Name – SONALI AGARWAL
Reg. No – 2024JULB00155
Major – Digital Business and Analytics / **Minor** – Finance
RFP Company – Deloitte
RFP Mentor – Prof. Sundar Raj Vijayanagar
Major Contribution to the project: She handled the data gathering and cleaning process. She collected both transactional and demographic datasets, checked for missing or incorrect values, and prepared the data for analysis. Her work ensured that all variables such as utilization ratio and repayment discipline were accurate and ready for modeling.

Name – SUBHAM KUMAR SAHANA
Reg. No – 2024JULB00161
Major – Digital Business and Analytics / **Minor** – Innovation Incubation
RFP Company – Deloitte
RFP Mentor – Prof. Sundar Raj Vijayanagar
Major Contribution to the project: He focused on the core analytical part of the project. He worked on customer segmentation using behavioural and demographic data, built predictive models to forecast credit utilization, and designed prescriptive strategies. His contribution helped identify different customer groups and suggest practical recommendations for risk control and growth.